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Spatio-Temporal Pattern Recognition with Evolving Spiking Neural Networks

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Content

1. ANN and Evolving Connectionist Systems (ECOS)

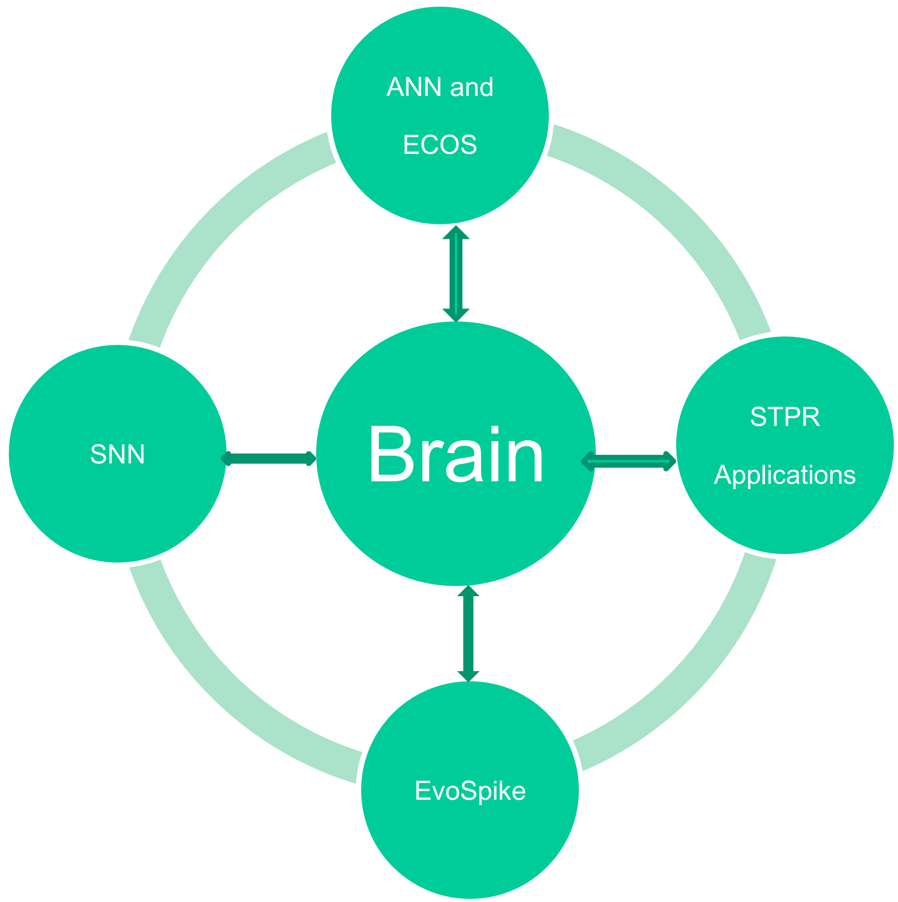
2. Spiking neural networks (SNN)

3. EvoSpike: eSNN for STPR

4. STPR Applications

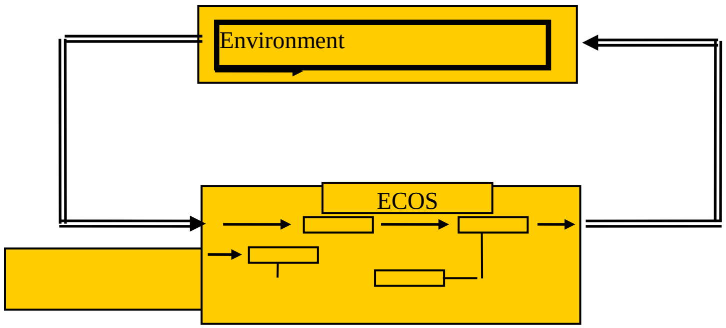
5. Future directions

6. References



1. ANN and Evolving Connectionist Systems (ECOS)

- ECOS are modular connectionist-based systems that evolve their structure and functionality in a continuous, self-organised, possibly on-line, adaptive, interactive way from incoming information, in a supervised and unsupervised way, facilitating knowledge discovery (Kasabov, 1998, 2002, 2007).



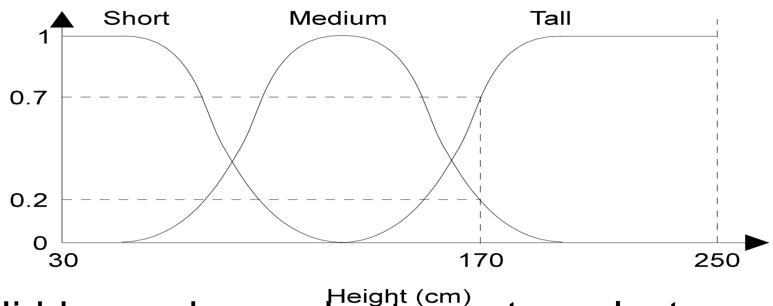
- Early ECOS models: RAN (J.Platt, 1991) – evolving RBF NN; Incremental FuzzyARTMAP (Carpenter , Grossberg); Growing gas; EFuNN (Kasabov, 1998, 2001); ESOM (Deng and Kasabov, 2002); DENFIS (Kasabov, Song, 2002); EFuRS, eTS (Angelov, 2002;Filev, 2002).

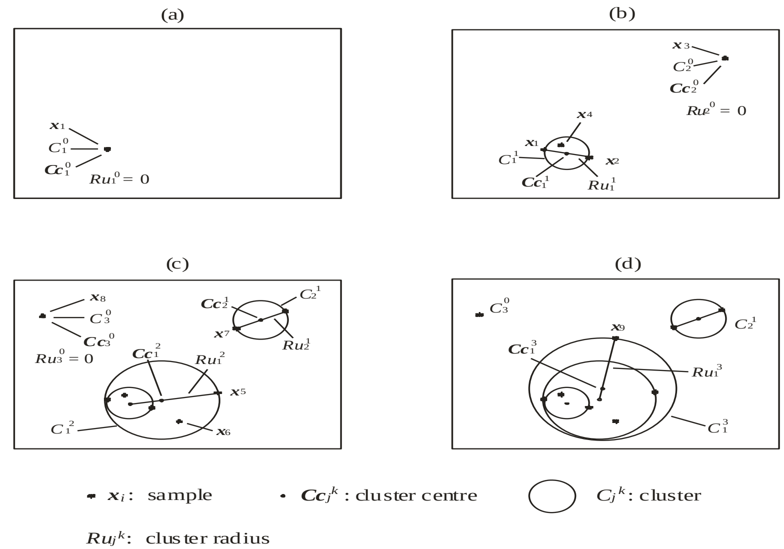
- M.Watts, *Ten years of Kasabov's evolving connectionist systems, IEEE Tr SMC- part B, 2008.*

- New developments: Ensembles of EFuNNs (T. Ljudemir, 2008-); Application oriented ECOS (B.Gabric, R.Duro, McGinitty et al.); Incremental feature selection (Ozawa, Pang, Kasabov, Polikar, Minhu Lee), other.

Ezamples: Evolving clustering metods, Evolving Fuzzy Neural Network (EFuNN), Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS)

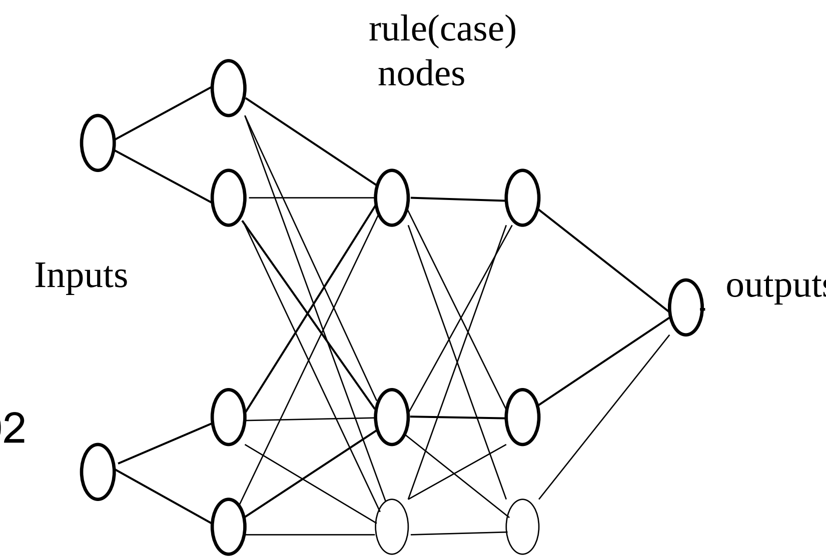
- Evolving clustering (ECM)
- Incremental, supervised clustering
- Input and/or output variables can be non-fuzzy (crisp) or fuzzy, e.g.:





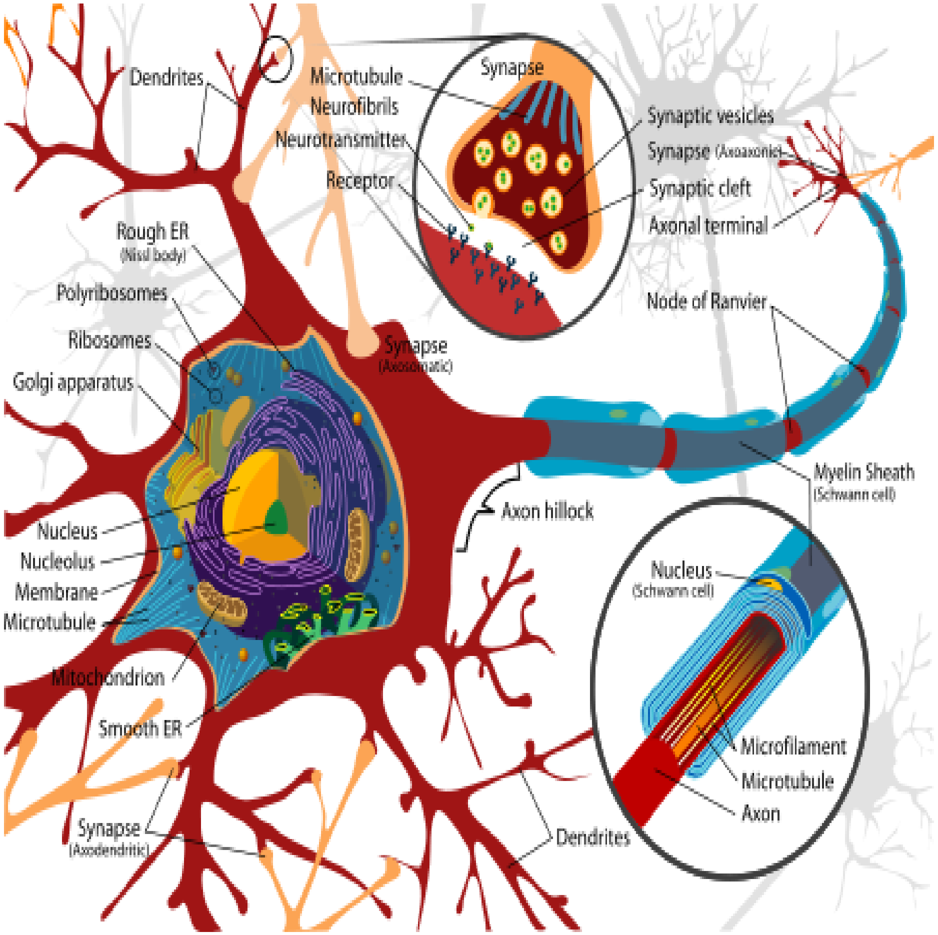
- Hidden nodes evolve to capture clusters (prototypes) of input vectors
- Input weights change based on *Euclidean distance* between input vectors and prototype nodes:

  Δ**w**=lrate * E(**x**, Rn)



- Output weights evolve to capture local output function and change based on error.
- EFuNN, N. Kasabov, IEEE Tr SMC, 2001
- DENFIS, N.Kasabov and Q.Song, IEEE FS, 2002
- ECOS Toolbox available in MATLAB (demo)
- NeuCom Software available: www.kedri.info

2. Spiking neural networks (SNN)



The mighty neuron!

A single spiking neuron is very rich of information processes: time; frequency; phase; field potentials; molecular (genetic) information; space.

Three, mutually interacting, memory types

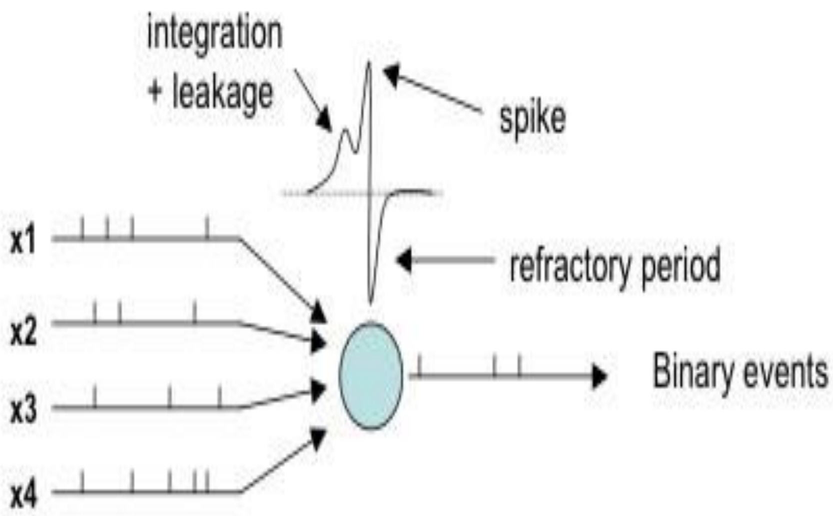
- short term;
- long term
- genetic

SNN can accommodate both spatial and temporal information as location of neurons/synapses and their spiking activity over time.

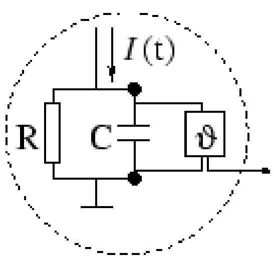
Generic methods for information processing in SSN have already been developed.

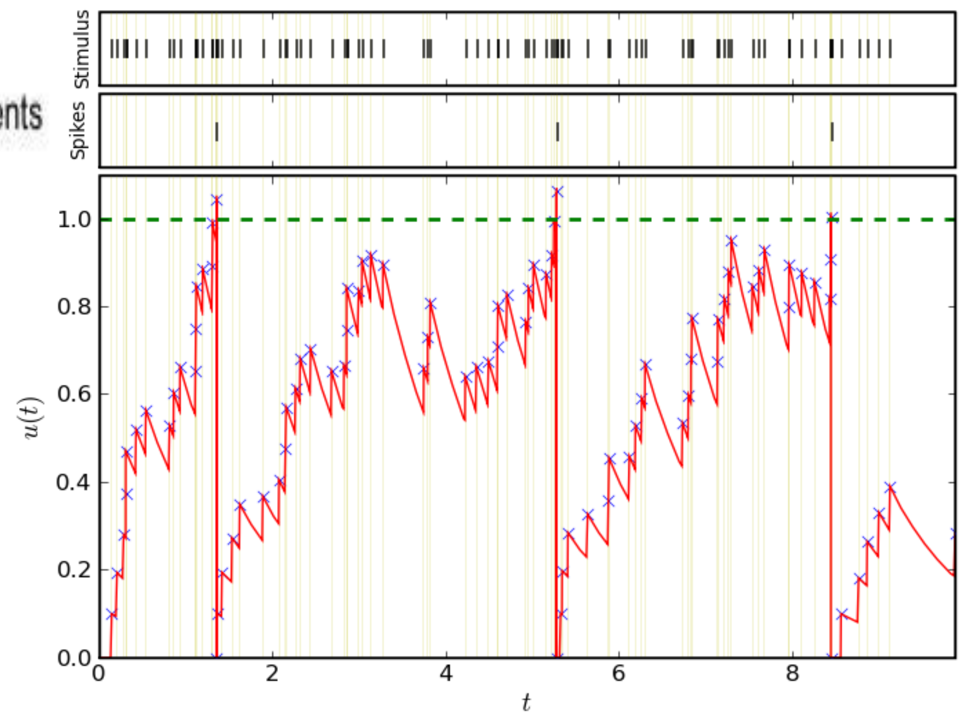
Models of spiking neurons:

(Hodgkin-Huxley 1952; Abbott, 2000; Maas, Izhikevich; other) .



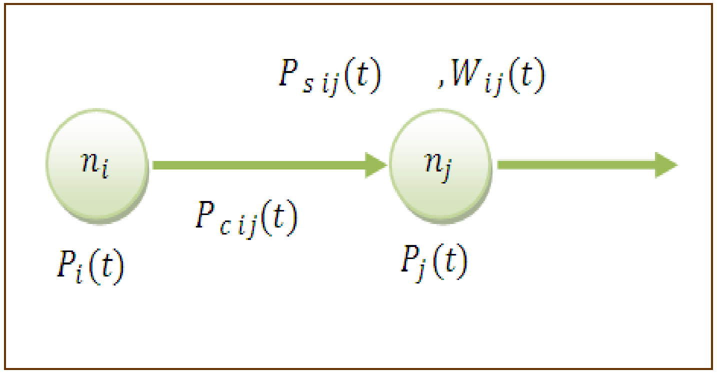
$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$





A probabilistic spiking neuron model – extension of the LIF

(Kasabov, Neural Networks, Jan. 2010)



The information is represented as both connection weights and probabilistic parameters.

The PSPi(t) is now calculated using a new formula:

$$PSP_i\,(t) = p_i(t) \sum_{p=t_0,..,t} \; \sum_{j=1,..,m} e_j\, g(p_{cj,i}(t-p))\, f(p_{sj,i}(t-p))\, w_{j,i}(t) - \eta(t-t_0)$$

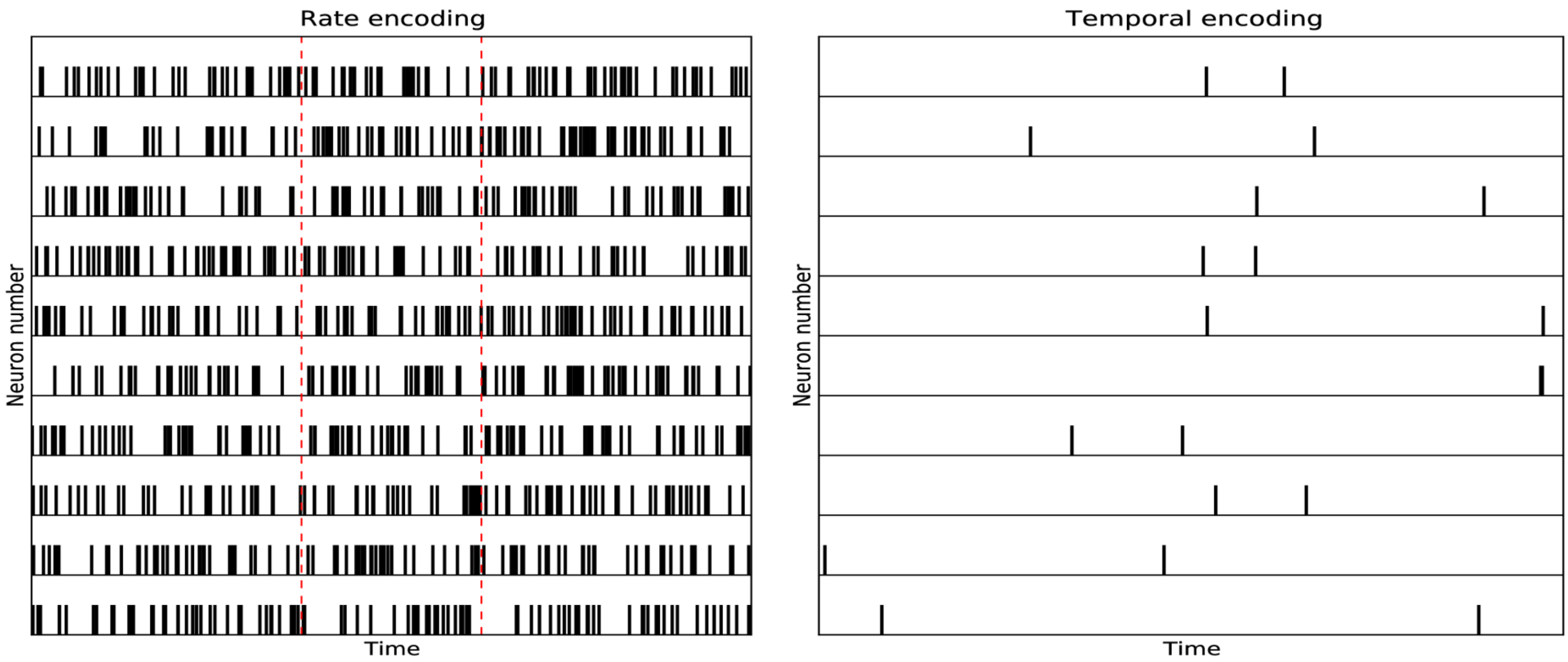
- $p_{cj,i}(t)$ is the probability that a spike emitted by neuron n_j will reach neuron n_i at a time moment *t;*
- probability $p_{sj,i}(t)$ of the synapse $s_{j,i}$ to contribute to the PSPi(t) after it has received a spike from neuron n_j
- probability $p_i(t)$ for the neuron n_i to emit an output spike at time *t* that depends on the total PSP_i (t) but also on a **noisy reset and threshold,**
- t_0 is the time of the last spike emitted by n_i;
- $\eta(t-t_0)$ is an additional term representing decay in the PSP.

As a special case, when all probability parameters are “1”, the pSNM is reduced to LIF model.

Rate - vs time-based coding of information as spikes

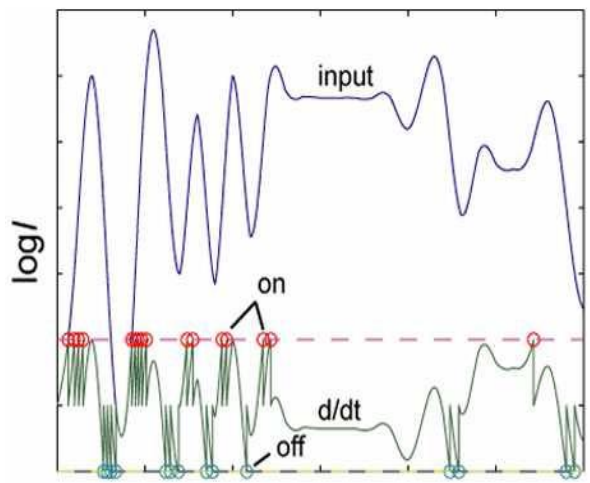
- Rate-based coding: A spiking characteristic within a time interval, e.g. frequency.

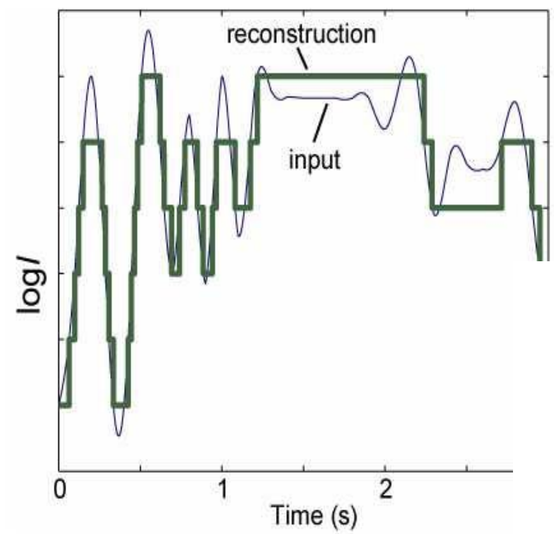
- Time-based (temporal) coding: Information is encoded in the time of spikes. Every spike matters! For example: class A is a spike at time 10 ms, class B is a spike at time 20 ms.

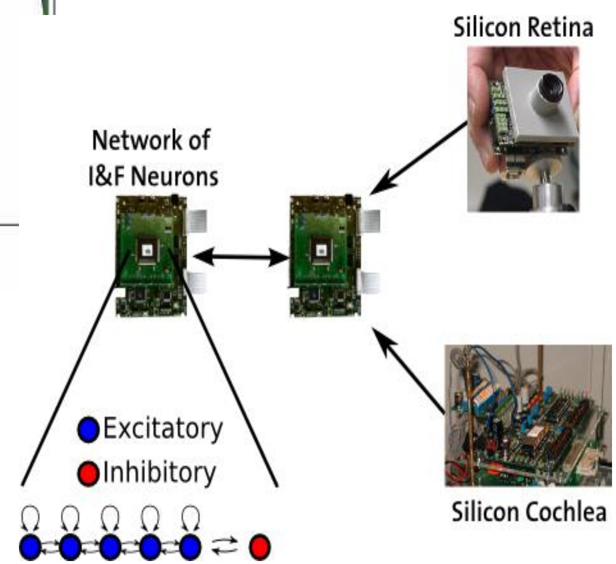


SNN: Input data encoding into spikes

Address event representation (AER):
Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128
Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich)



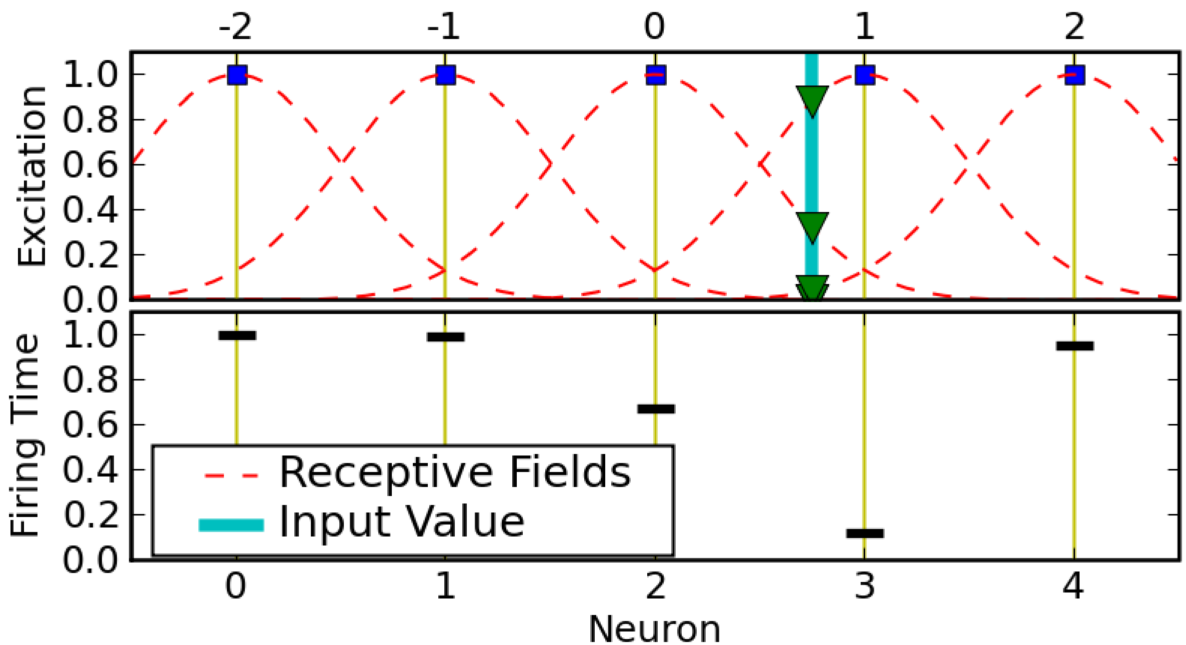




SNN: Rank order population coding (RO-POC)

- A single real input value is distributed to multiple neurons and may cause the excitation and firing of several responding neurons at different times

- Implementation based on Gaussian receptive fields introduced by Bothe *et al*. 2002



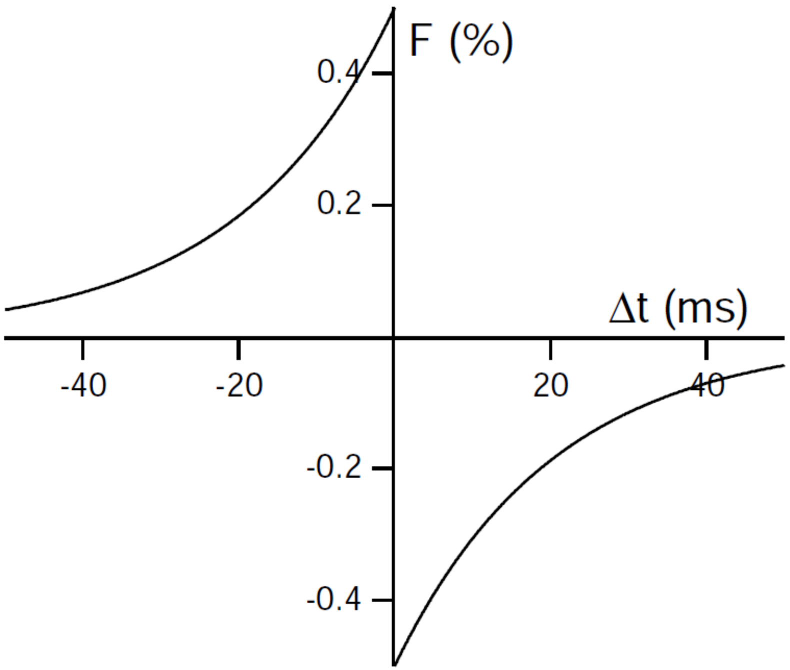
$$\mu = I_{\min} + (2*i-3)/2*(I_{\max} - I_{\min})/(M-2)$$

Methods for learning in SNN:
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

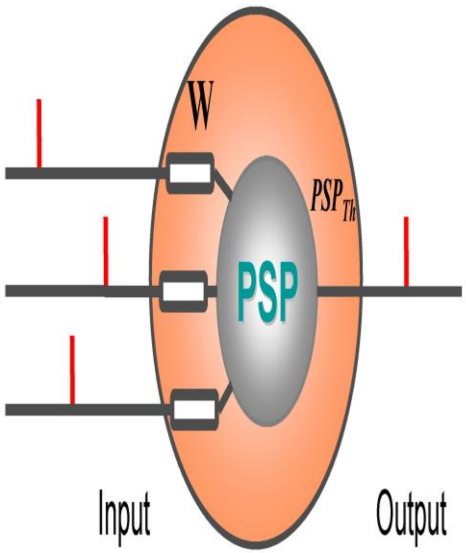
- Hebbian form of plasticity in the form of long-term potentiation (LTP) and depression (LTD)
- Effect of synapses are strengthened or weakened based on the timing of pre-synaptic spikes and post-synaptic action potential.
- Through STDP connected neurons learn consecutive temporal associations from data.

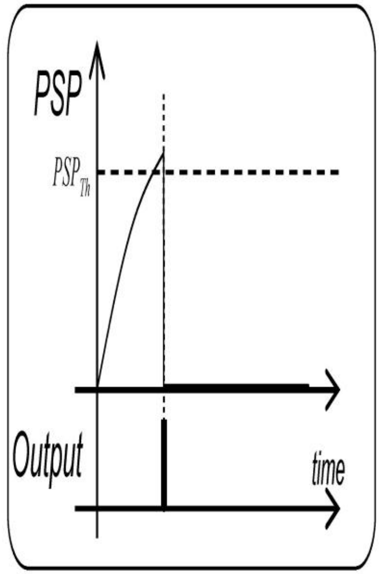
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD

Δt=tpre -tpost



The rank order (RO) learning rule
(Thorpe et al, 1998)





$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\mathrm{order}(j)} & \text{else} \end{cases}$$

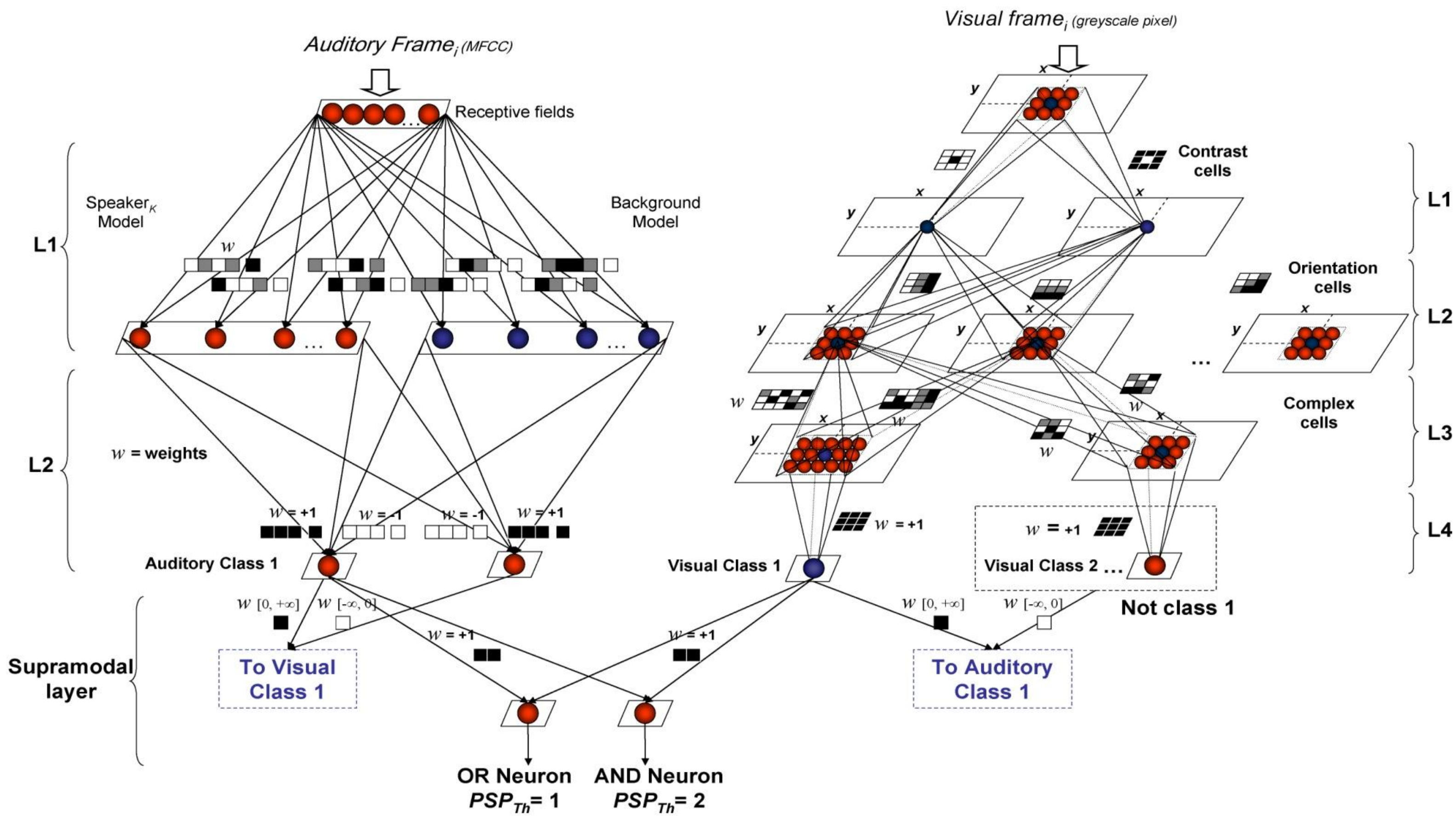
PSP max = SUM (mod $^{\mathrm{order}\,(j,i(t))}$ $w_{j,i}(t)$), for j=1,2.., m; t=1,2,...,T

PSP_{Th}=C. PSPmax

Evolving SNN (eSNN)
Example: Integrated audio-visual information processing

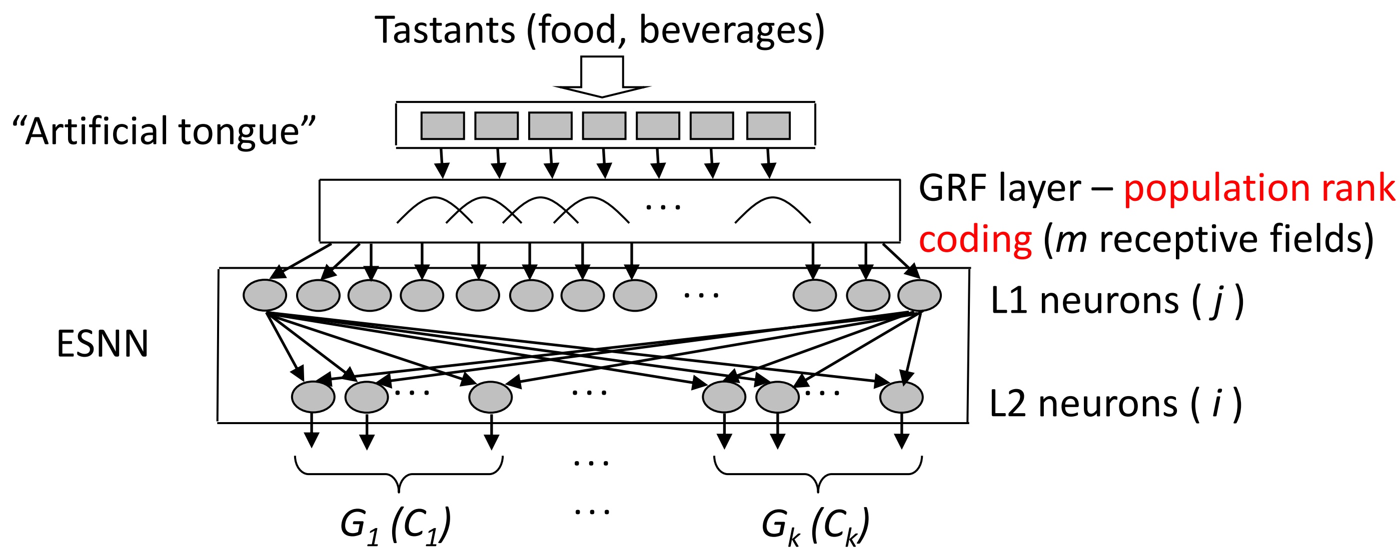
Person authentication based on speech and face data

(Wysoski, Benuskova and Kasabov, *Neural Networks*, 2010)



Example: eSNN for classification of tastes

(Soltic, S.Wysoski and N.Kasabov, Proc.WCCI 2008, Hong Kong)

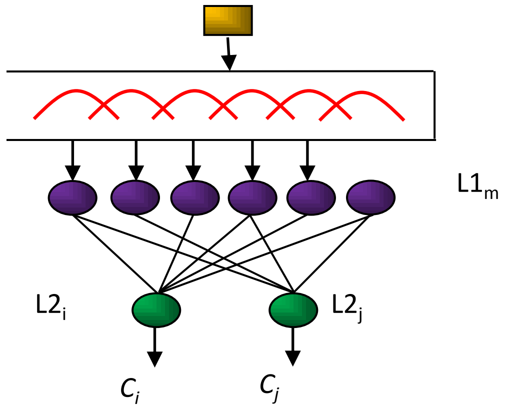


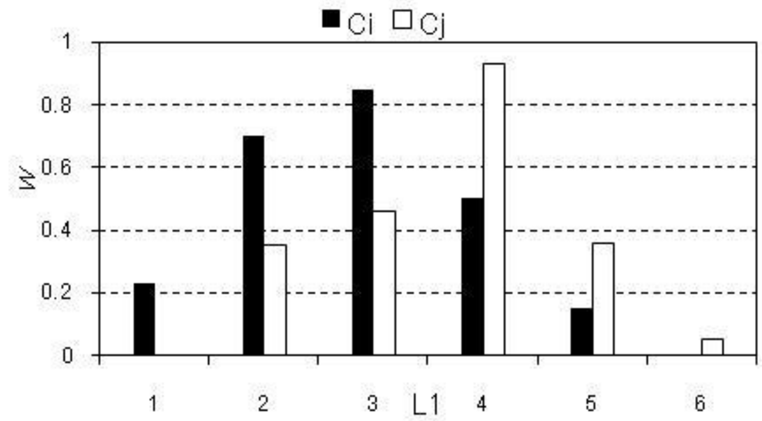
Other examples:

- **Ecological modelling** (Schliebs et al, IJCNN, 2010)
- **Face and mood recognition** (H-G.Hou et al, IJCNN 2011)
- **Speech and image recognition** (McGinnity et al, Ulster)

Methods for fuzzy rule extraction from eSNN

(S.Soltic, N.Kasabov, Int. J. Neural Systems, World Sc. Publ., 2010)

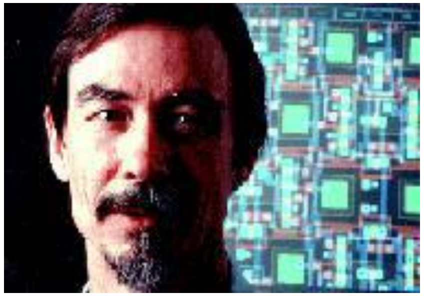




$$IF \quad v \text{ is } SMALL \quad THEN\ C_i$$

$$IF \quad v \text{ is } LARGE \quad THEN\ C_j$$

Technological progress in neuromorphic computation



Hodgin- Huxley model (1952)

Carver Mead (1989): A hardware model of an IF neuron:
The Axon-Hillock circuit;

INI Zurich SNN chips (Giacomo Indivery, 2008 and 2012)

FPGA SNN realisations (McGinnity, Ulster, 2010);

The IBM chip (D.Modha, 2012): 256 LIF neurons and 64k synapses in a chip.

U. Manchester SpiNNaker (2^{16} computer chips, 2011; 1 mln neurons 2013)

Stanford U., NeuroGrid (Kwabena Boahen et al), 1mln neurons on a board, 63 bln connections ; hybrid - analogue /digital)

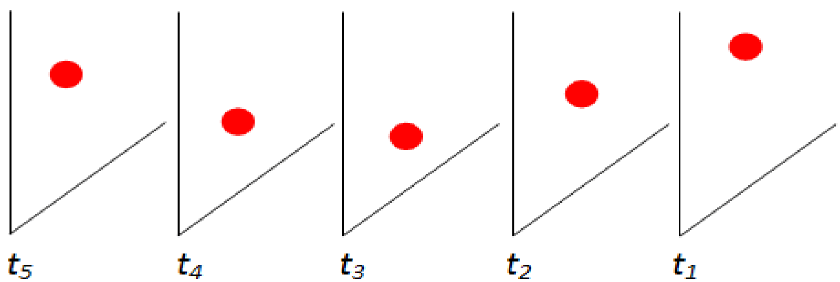
The challenge: Technology is available, but how do we use it for STPR ?

3. EvoSpike: eSNN for STPR problems.

Examples of STPR problems:

a) Object movement recognition from video data
b) Audio/video data modelling
c) Brain signals (EEG, MEG, fMRI)
d) Brain- computer interfaces
e) Motor control for prosthetics
f) Ecological and environmental data, e.g. earthquake prediction
g) Robot control
h) Cyber-security data

- In STPR problems spatial and temporal components of the information are interrelated.

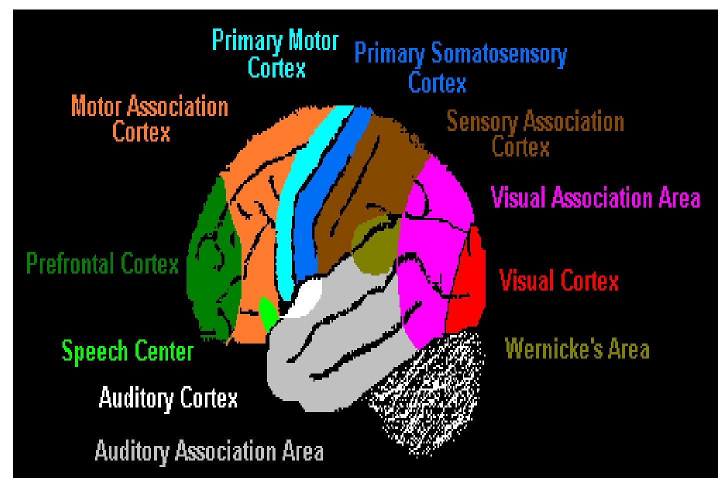


Spatio-temporal input data

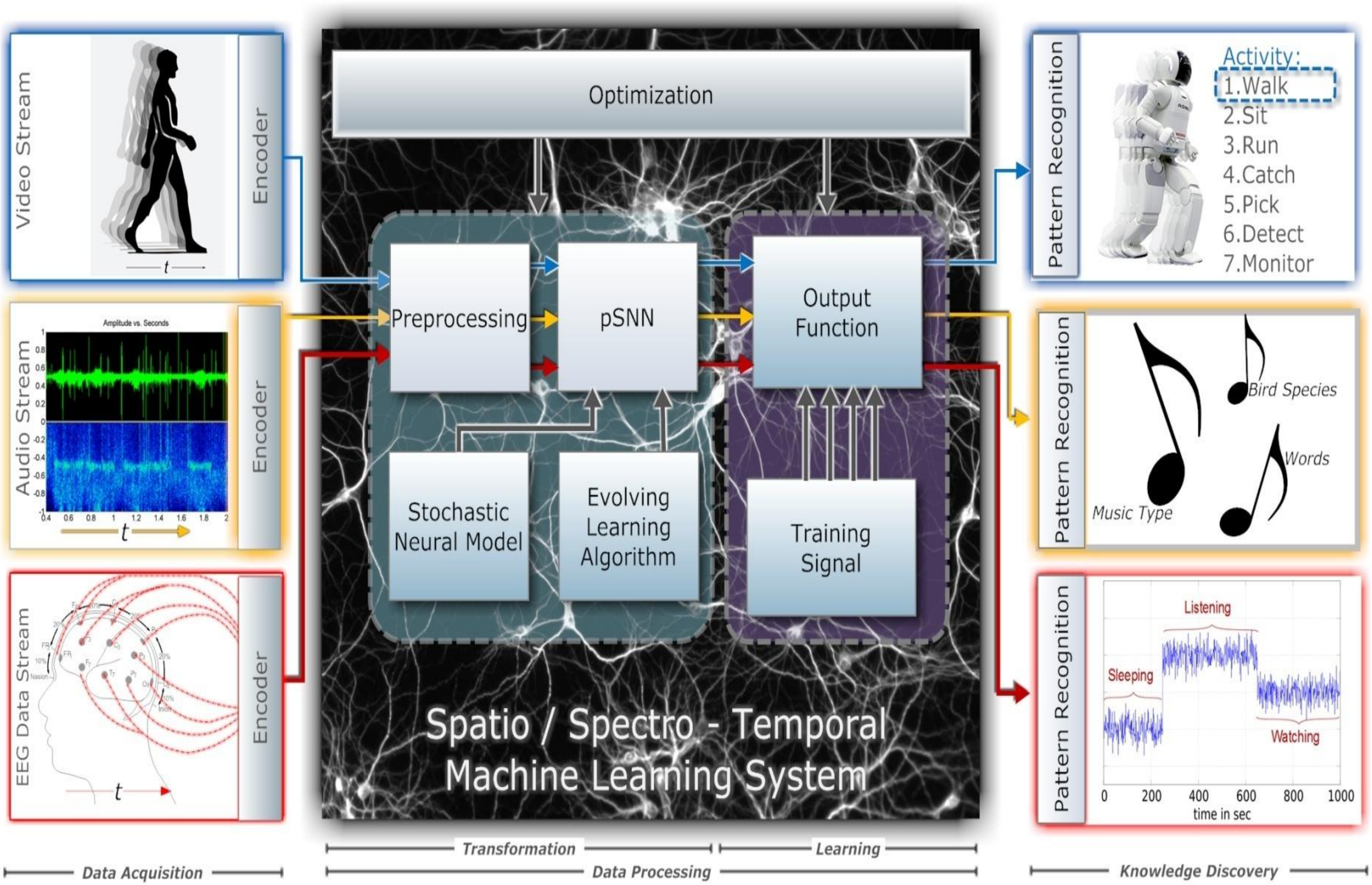
Existing techniques are not efficient for STPR

- Standard CI techniques: designed for static data (e.g. MLP, SVM, regression); trained and recalled vector by vector, frame by frame
- Time delayed NN: fixed number of time lags, but how many are optimal for the current time?
- Hidden Markov Models: require large training data for probability estimation;
- With the increased understanding of the brain processes, more brain-like *deep machine learning* methods are proposed: HMAX; Neocognitron (Fukushima). They are good for static data (e.g. images) rather than for SSTD (video data, event-based and dynamic data).

- Inspiration might come from:
  - How the brain learns SSTD, event by event.
  - How it stores ‘time’.



The EvoSpike Architecture



EvoSpike Objectives

- Explore different input encoding schemes and devices, e.g. artificial retina, artificial cochlea.

- Develop new learning algorithms suitable for STPR

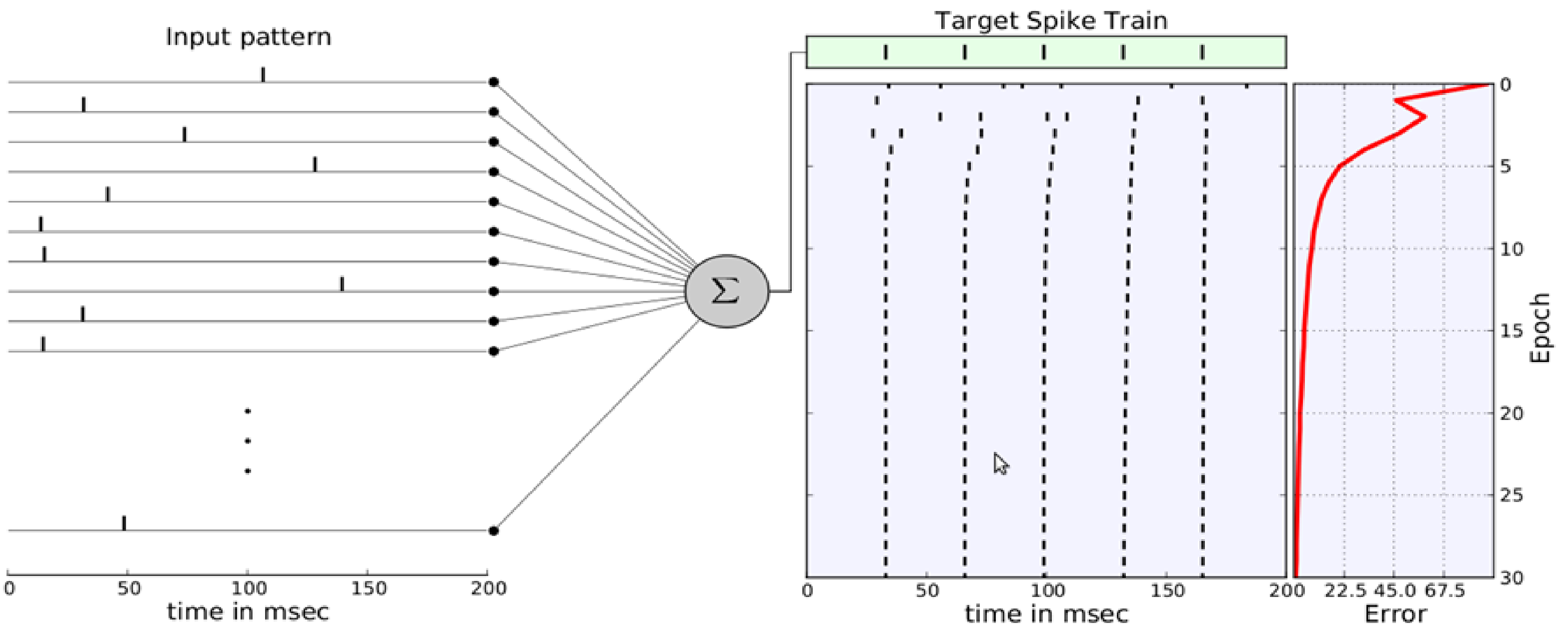
- Develop methods to optimize parameters and neuronal connections using through evolutionary optimisation (e.g. quantum inspired GA; QiPSO; Gene Regulatory Networks (GRN).

- Apply EvoSpike to solve difficult AI problems: complex object movement recognition; sound recognition; EEG data classification; brain state recognition from fMRI; ecological and environmental modelling; cybersecurity; autonomous robots; neuro-prosthetics; modelling AD.

    - Develop software/hardware implementations.

SPAN: Spike Pattern Association Neuron and the Delta Rule

(A.Mohhemed et al, EANN 2011, ICONIP2011, IJNS, 2012; Neurocomputing, 2012))



A single output neuron is trained to respond with a temporally precise output spike train to a specific spatio-temporal input.

Spike pattern association neuronal models: SpikeProp; ReSuMe; Tempotron; Chronotron.

SPAN delta learning rule

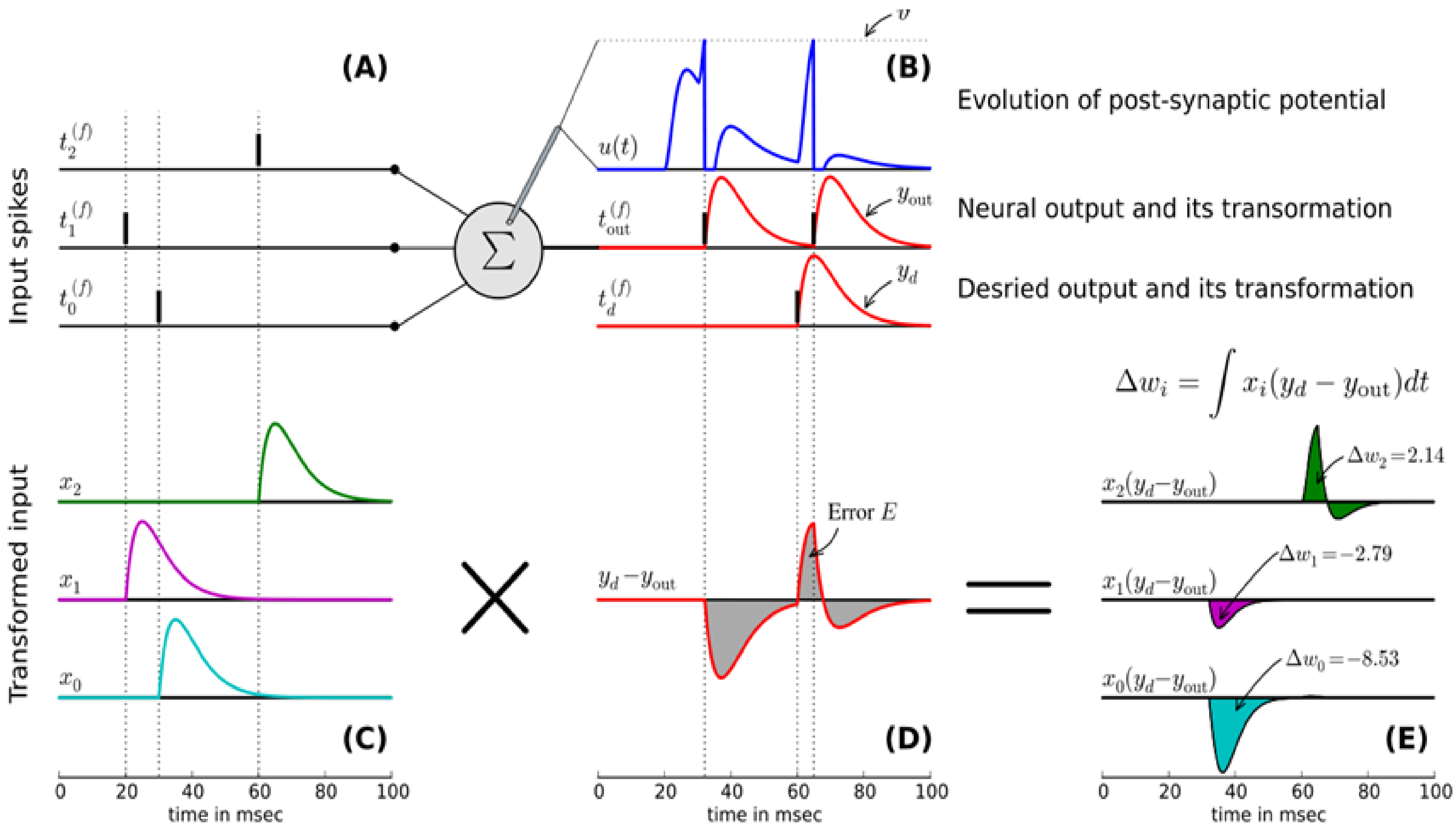


Illustration of the proposed training algorithm.

A single SPAN for spatio-temporal pattern classification

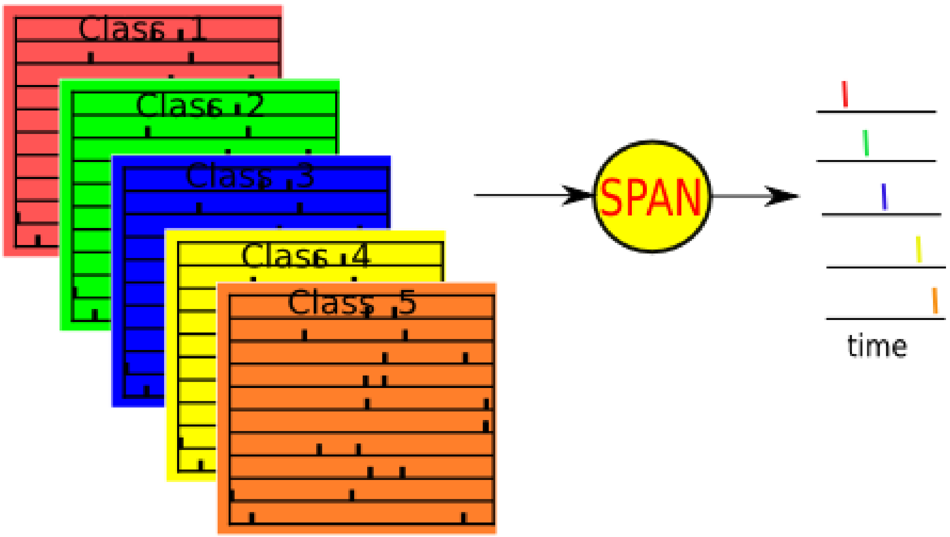
(Mohemmed, Schliebs, Matsuda and Kasabov, Int J Neural Systems, 2012)

- The objective is to learn to classify five classes of input spike patterns

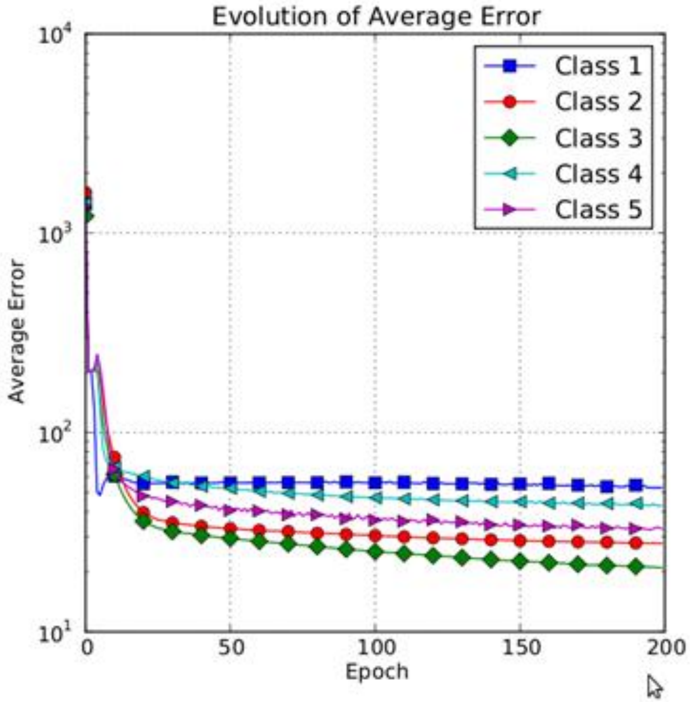
- The pattern for each class is generated randomly.

- Fifteen copies for each of the five patterns generated by perturbing each pattern using a Gaussian jitter with a SD of 3ms → 15 × 5 = 75 samples for training

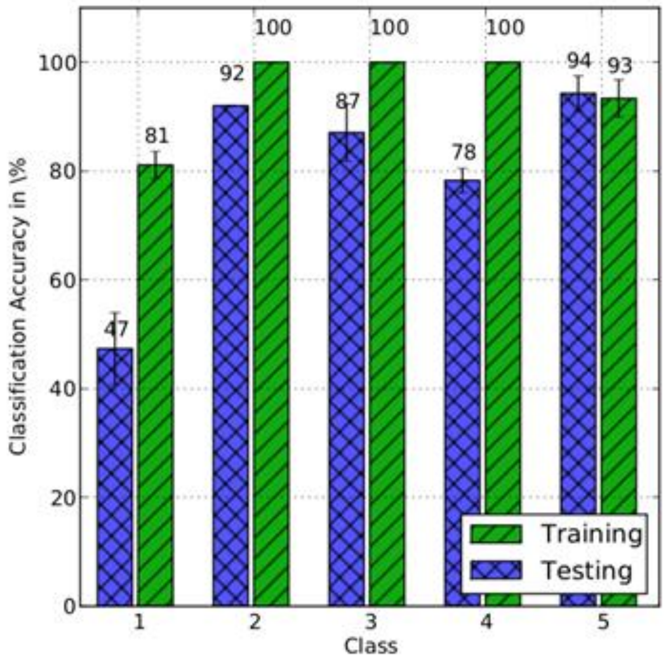
- Testing samples 25 × 5 = 125



A single SPAN classification results



(a)

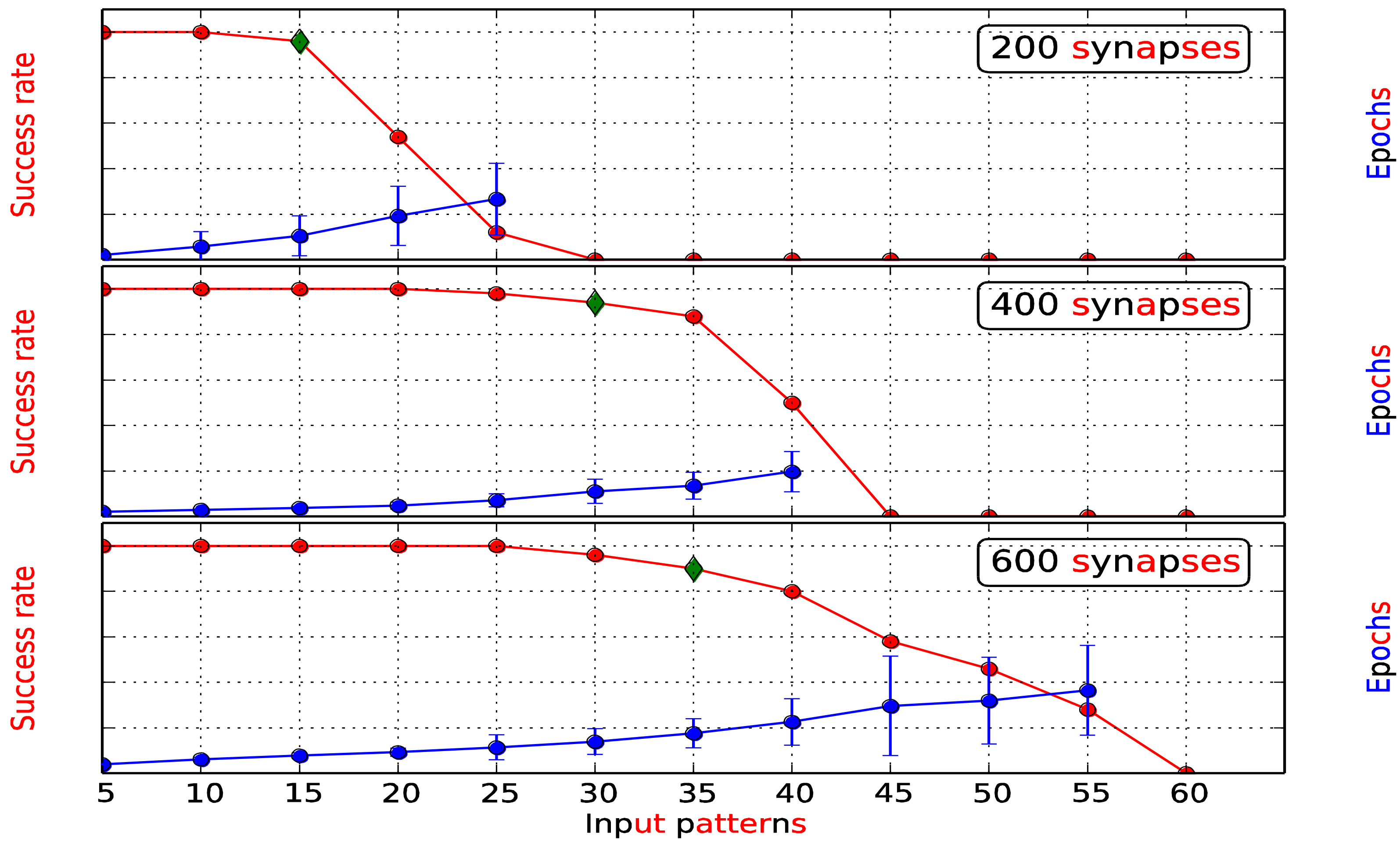


(b)

Evolution of the average errors obtained in 30 independent trails for each class of the training samples (**a**). The average accuracies obtained in the training and testing phase (**b**).

What is the memory capacity of a single SPAN?

(Mohemmed et al, Int J. Neural Systems, 2012)



Dynamic Evolving SNN (deSNN)

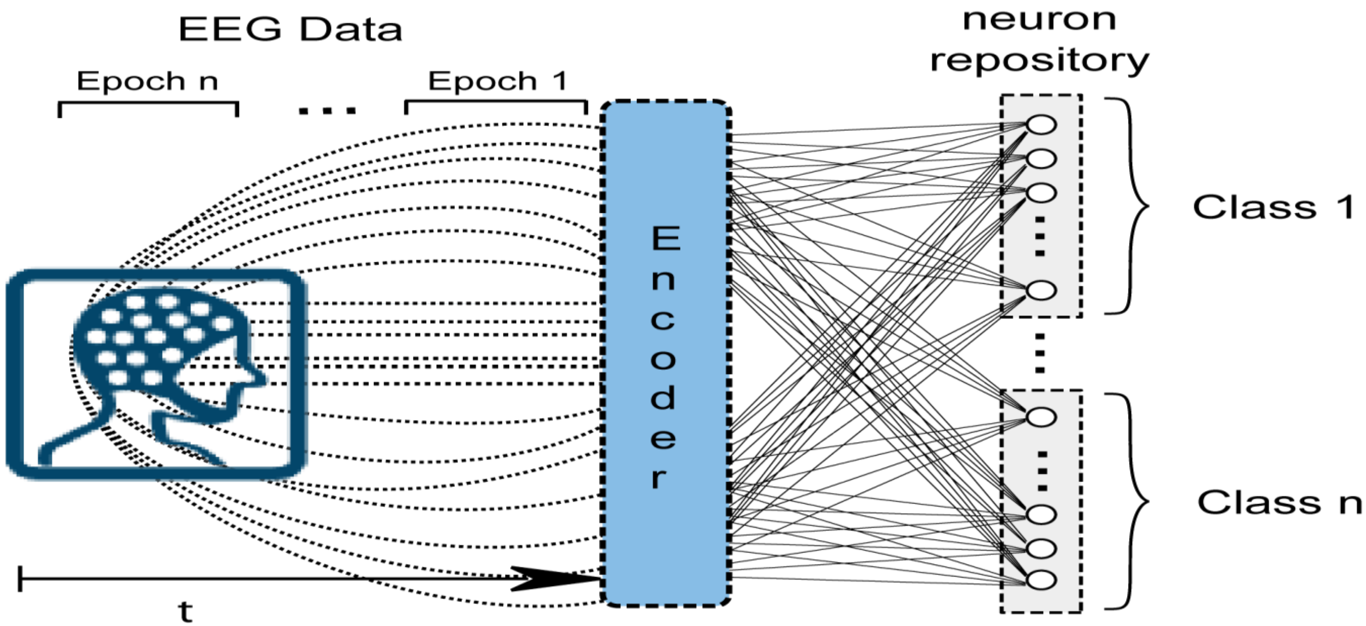
(Kasabov, Dhoble, Nuntalid, Indivery, WCCI 2012 and Neural Networks, 2012)

- Combine: (a) RO learning for weight initialisation based on the first spikes:

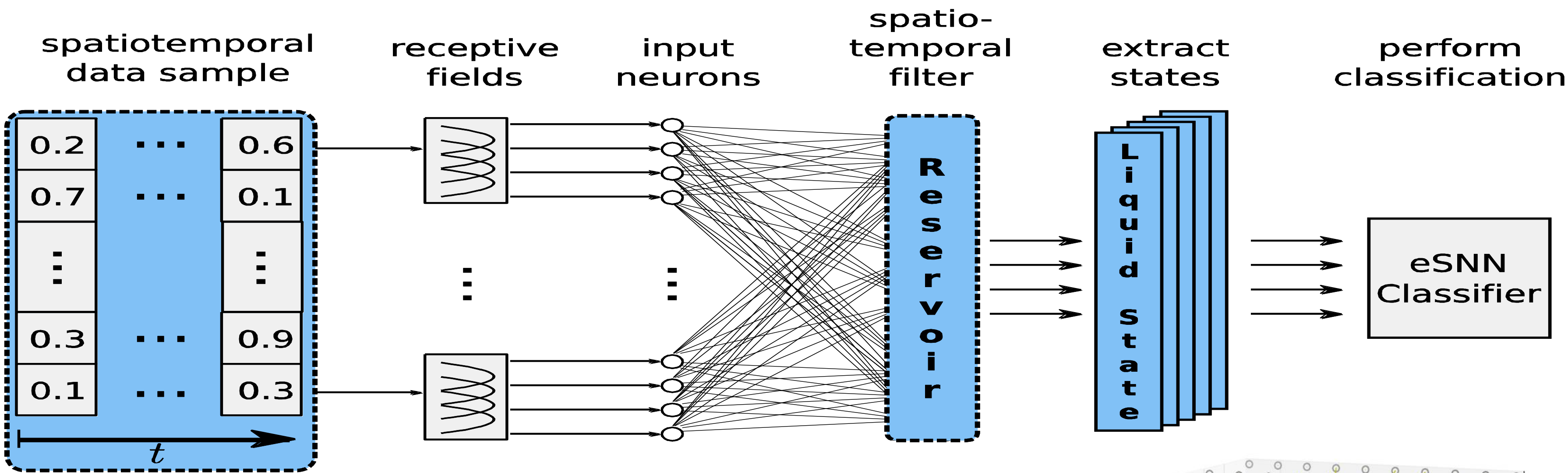
$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

(b) SDSP for learning further input spikes at a synapse.

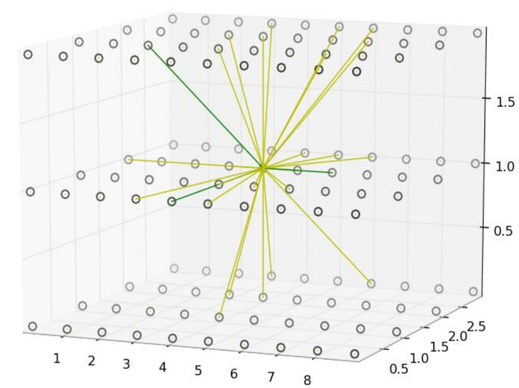
- A new output neuron is added to a respective output repository for every new input pattern learned. Neurons may merge.
- The figure below shows the deSNN architecture on a case study for EEG STPR.



Reservoir-based SNN



- *Maass, W., Natschl ̈ager, T., Markram, H.: Real-time computing without stable states, Neur. Comp. 14(11),2002;*
- Input (feature) neurons connected to part of the LSM
- Output neurons connected to part of the LSM
- LSM recurrent connections, e.g. small world connections
- Excitatory 80%, Inhibitory 20%
- Learning in LSM: STDP; spike time delay ....???
- Polychronization (Izhikevich): ‘opening the box’?

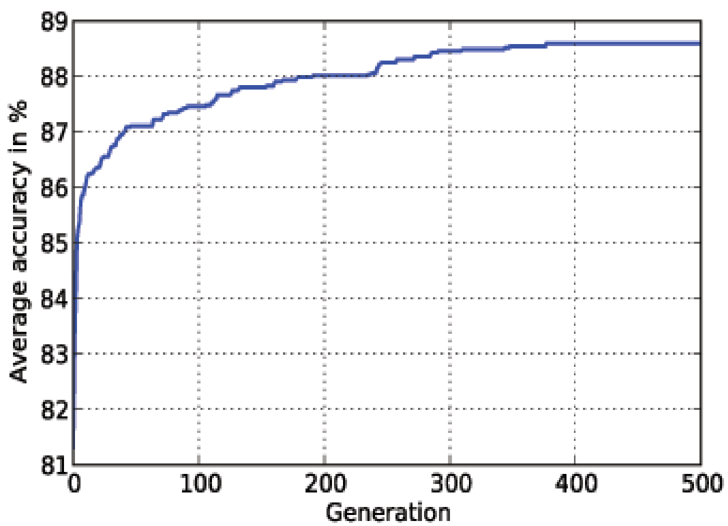


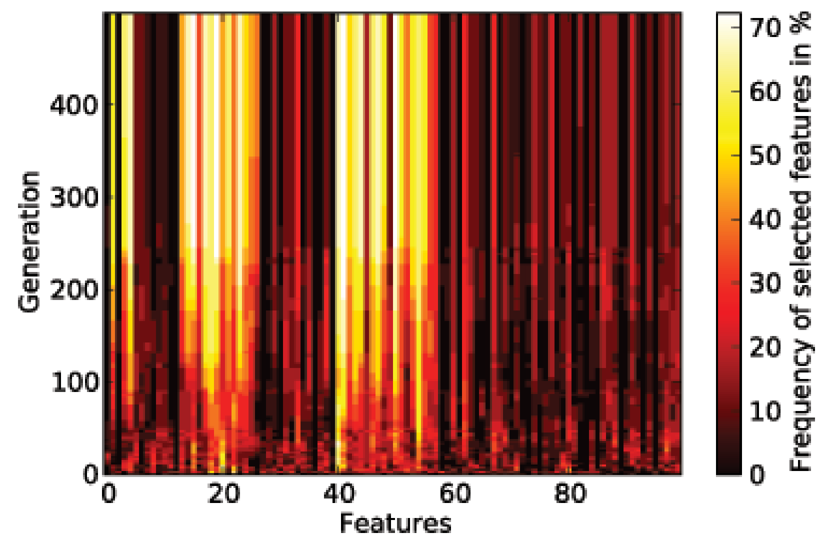
$$p_{a,b} = C \times e^{-D^2_{a,b}/\lambda^2}$$

eSNN Parameter Optimisation

A major issue in the EvoSpike model and system development is how to optimize the numerous epSNN parameters. Here we combine local learning of synaptic plasticity with global optimisation of probability and other parameters.

Example of using Dynamic Quantum Inspired Particle Swarm Optimisation (DQiPSO) (Hamed and Kasabov, 2011) to optimise together the features and the parameters of the reservoir eSNN (mod, C, Sim) for the LIBRAS STPR task

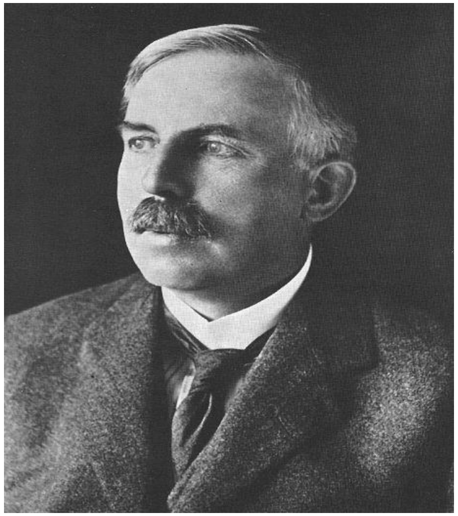




Why quantum inspired methods for evolutionary computation?

- Quantum principles: superposition; entanglement, interference, parallelism
  - Quantum bits (qu-bits)

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \qquad |\alpha|^2 + |\beta|^2 = 1$$



- - Quantum vectors (qu-vectors)

$$\left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{array}\right]$$

- Quantum gates

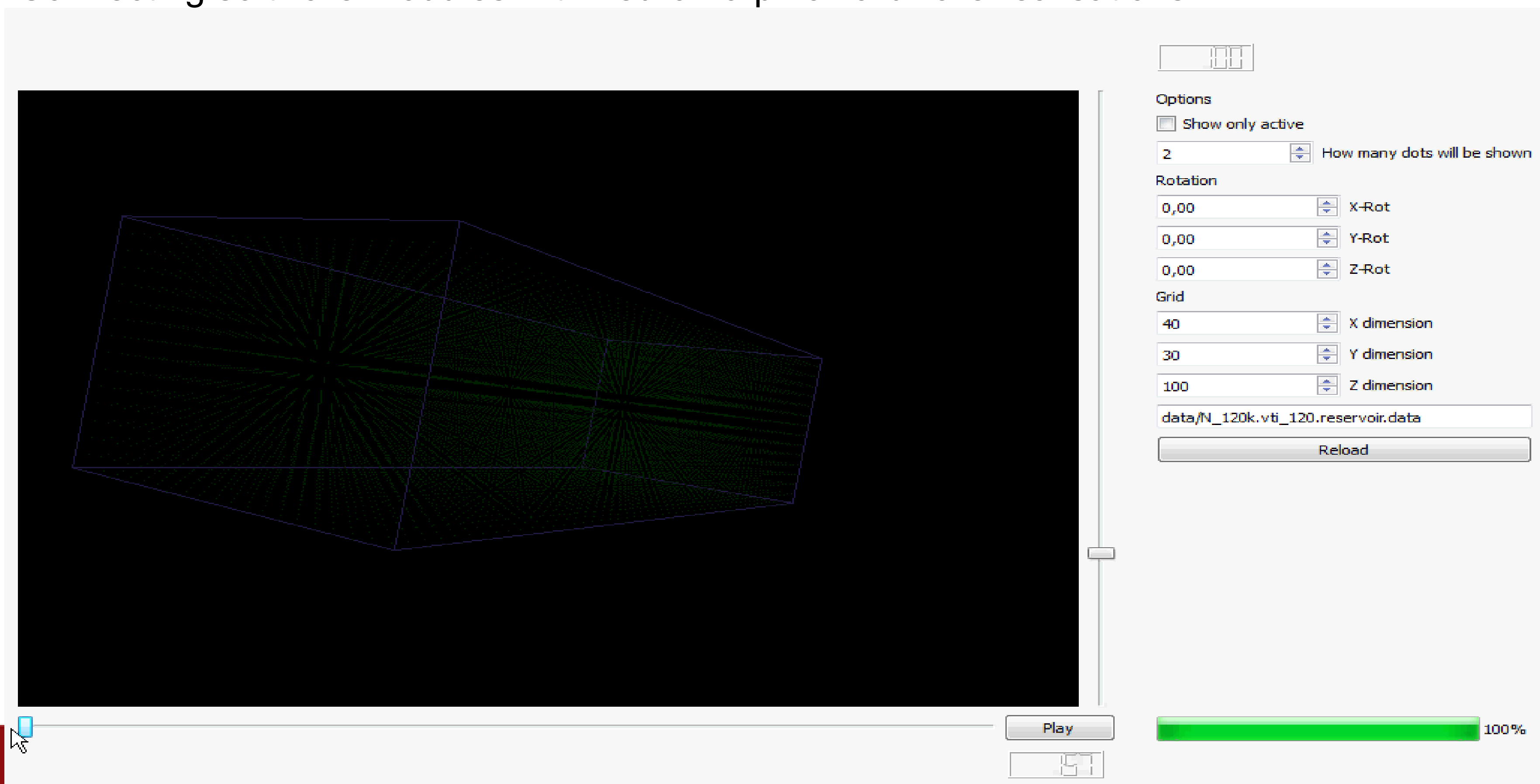
$$\begin{bmatrix} \alpha_i^j(t+1) \\ \beta_i^j(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i^j(t) \\ \beta_i^j(t) \end{bmatrix}$$

- Applications:
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), $O(N^{1/2})$ vs $O(N)$ complexity)
  - Quantum associative memories
  - Quantum inspired evolutionary algorithms and neural networks

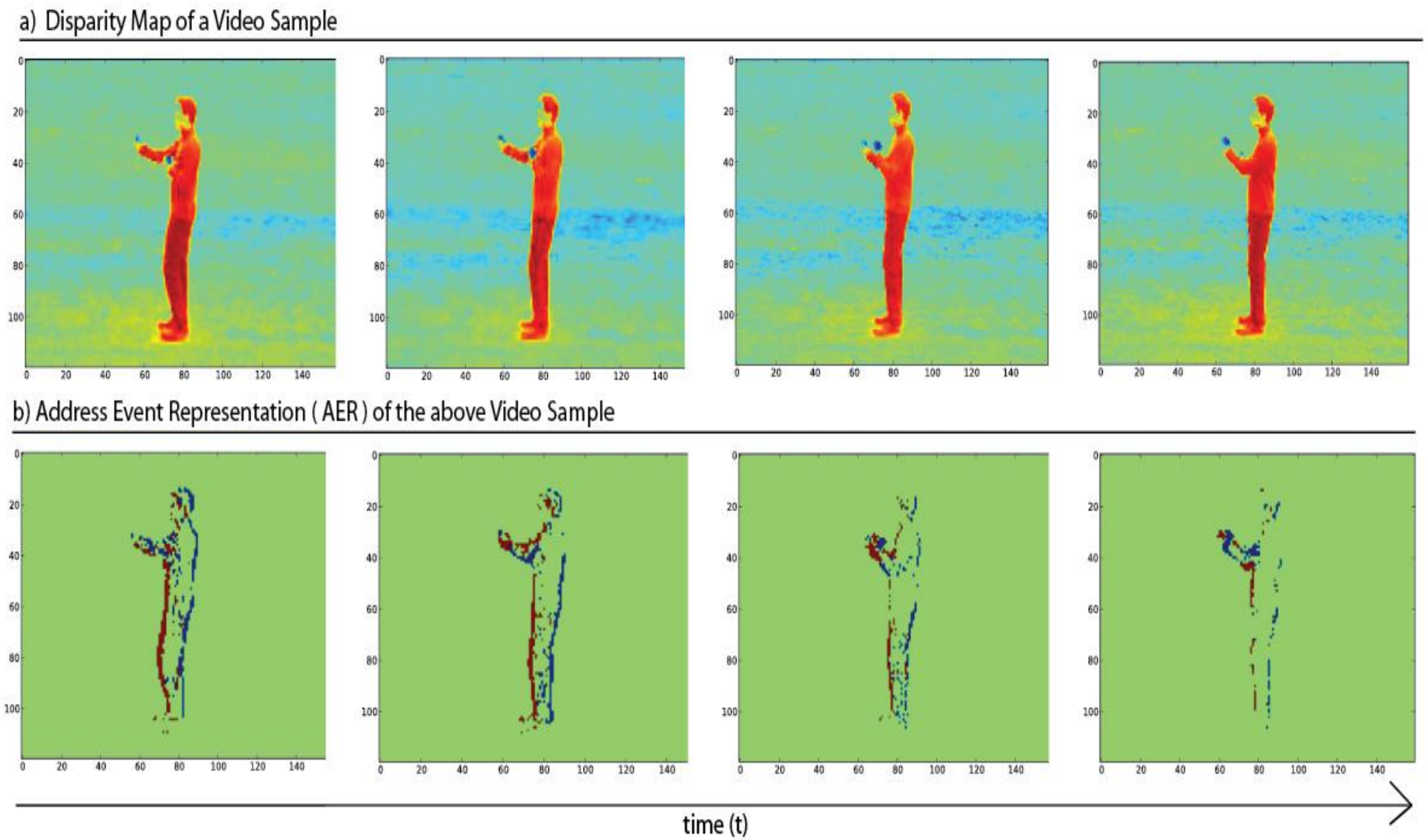
The EvoSpike Simulator

A collection of modules and functions written in Python language using functions from the Brian library for:

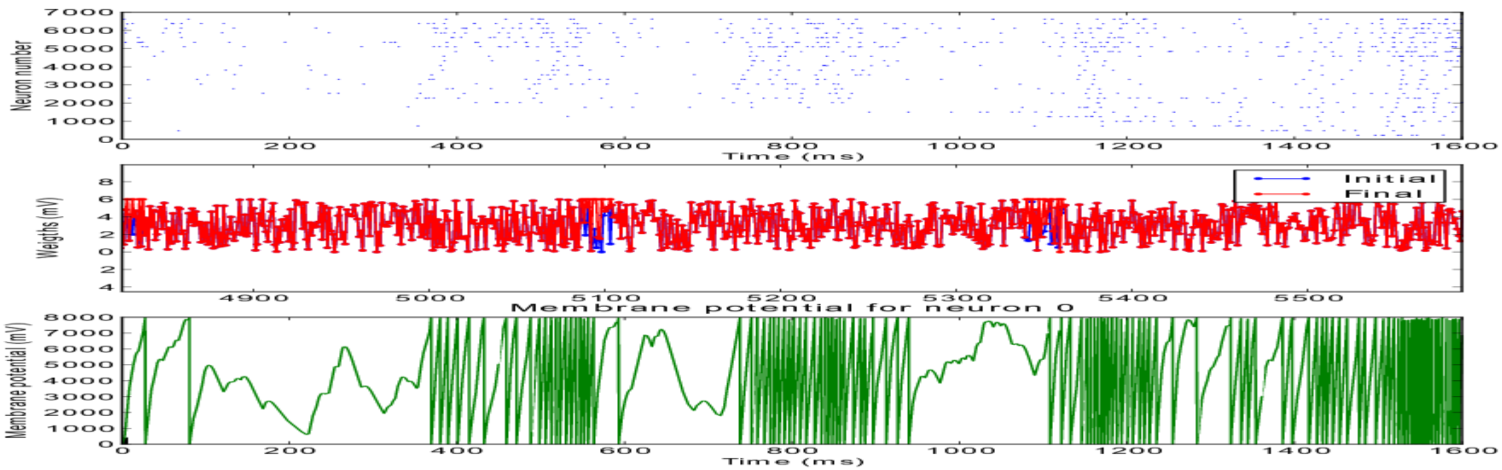
- Converting continuous-value input data into spike trains;
- SNN for spatio-temporal pattern recognition;
- Knowledge extraction from trained epSNN;
- Presenting results and visualisation of learning processes in the epSNN;
- Connecting software modules with neuromorphic hardware realisations.



4. STPR **Applications**
Moving object recognition using AER



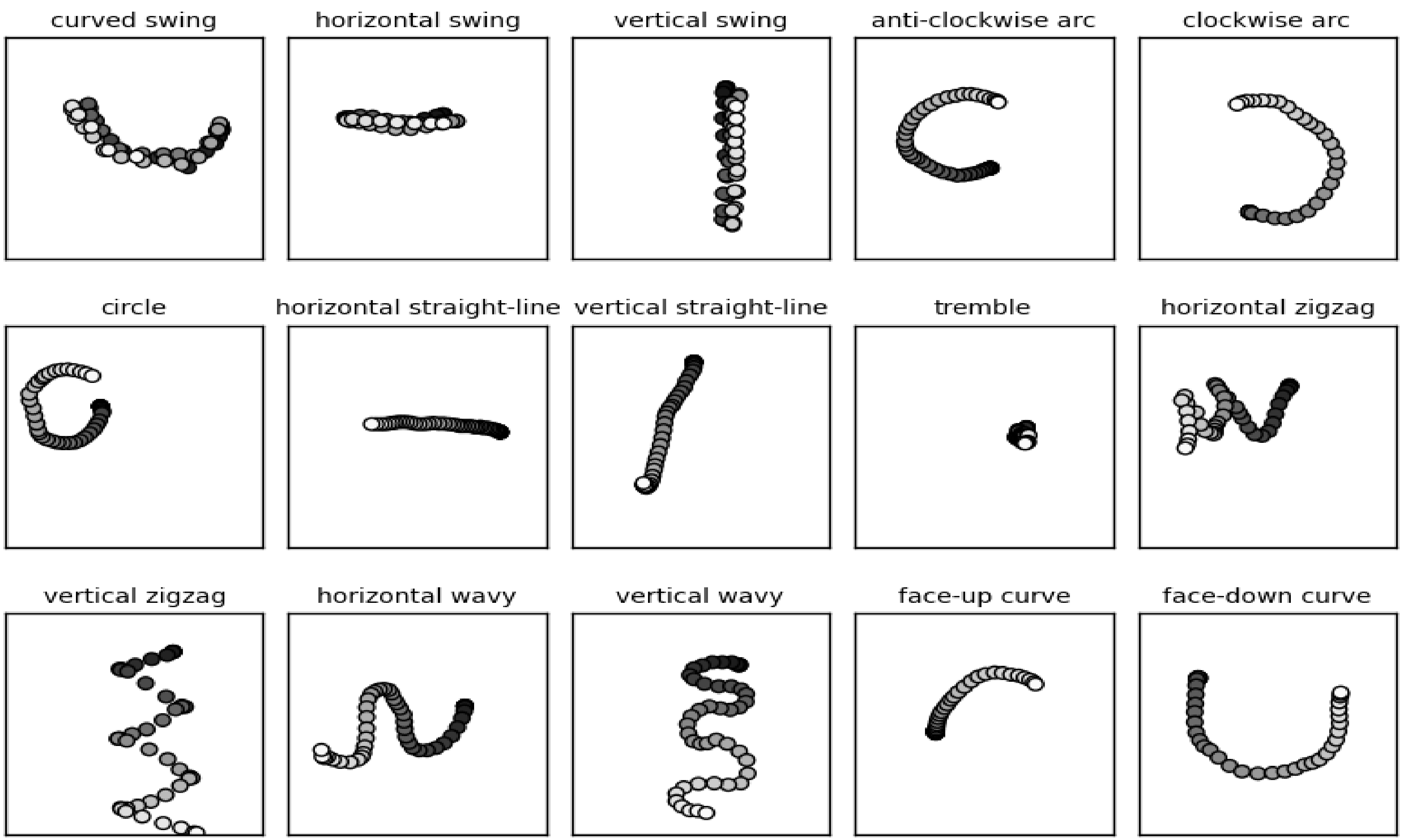
Moving object recognition using AER and deSNN for colision avoidance
(Kasabov, Dhoble, Nuntalid, Indivery, WCCI2012 and NN 2012)



The spike raster plot of a single AER of a STP of class „crash" (top figure; the dots represent spikes of 7000 input neurons representing spatially distribute pixels over 1600msec), and also the changes of the weights (middle figure) and the membrane potential (low figure) for output neuron 0 during the one pass learning in a deSNNs .

Model	SSDSP SNN	eSNNs	eSNNm	deSNNs	**deSNNm**
Classification accuracy	70%	40%	60%	60%	**90%**
No of training iterations	5	1	1	1	**1**

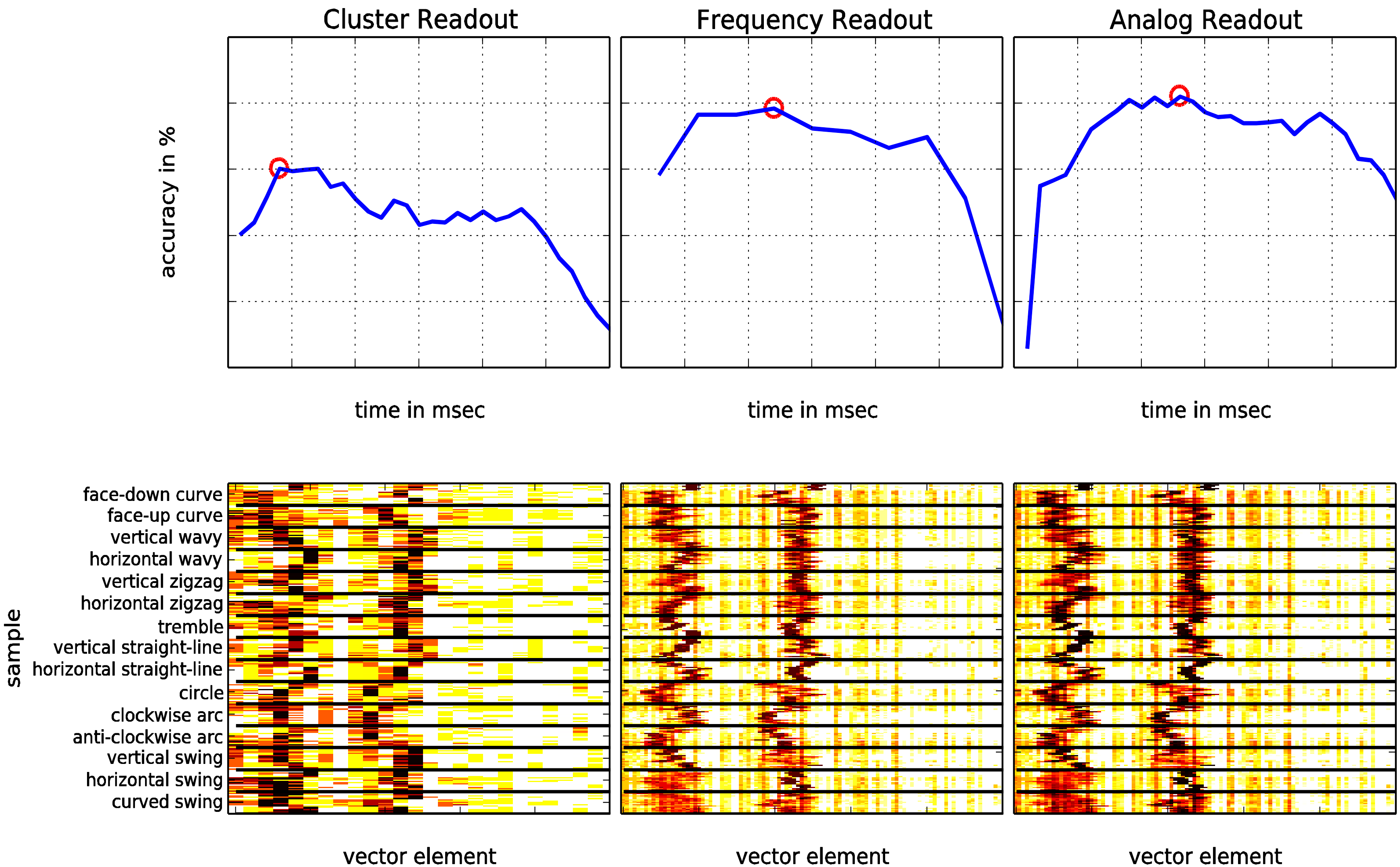
Brazilian sign language (LIBRAS) recognition



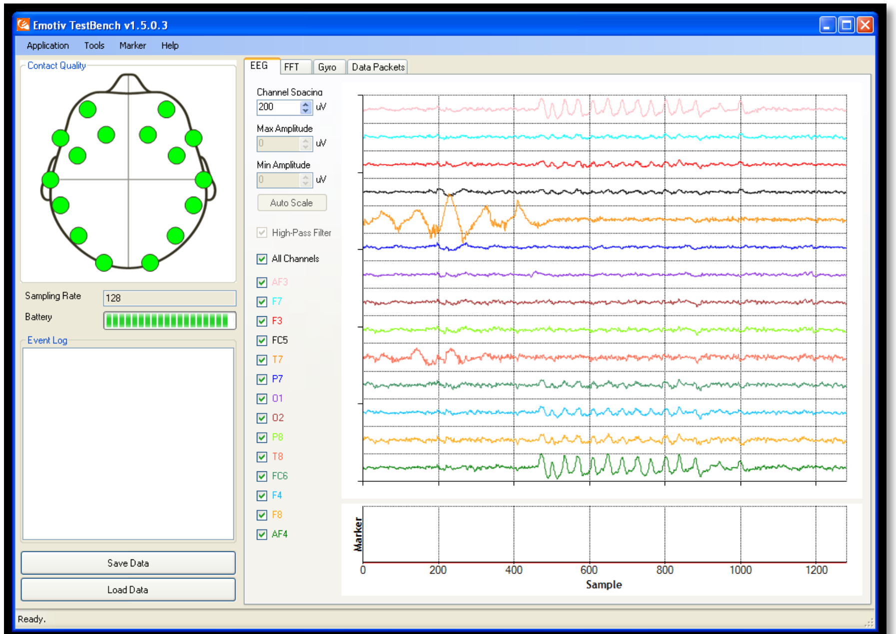
A single sample for each of the 15 classes is shown. The color indicating the time frame of a given data point (black/white corresponds to earlier/later time points).

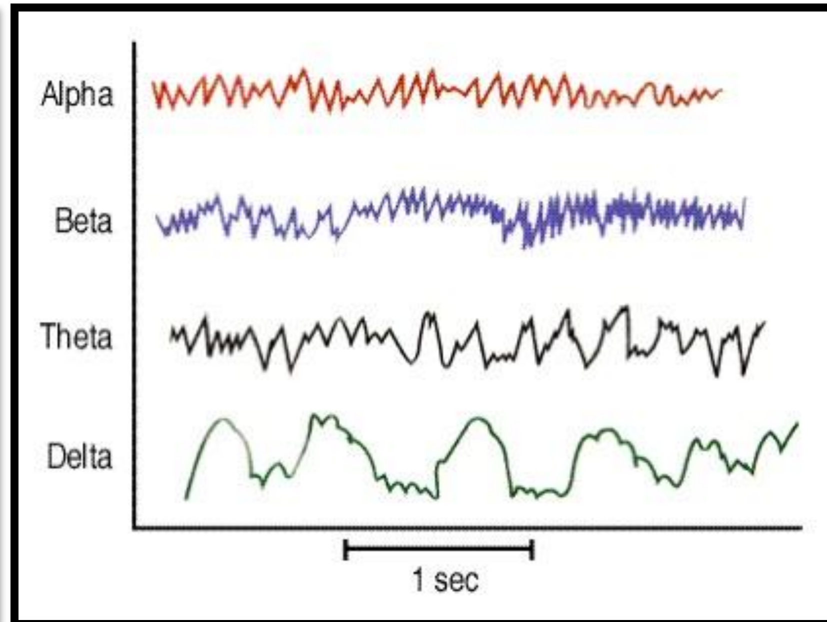
LIBRAS recognition with LSM reservoir and eSNN classifier using different methods to read the state of the LSM

(Schliebs, Nuzlu and Kasabov, ICONIP 2011)

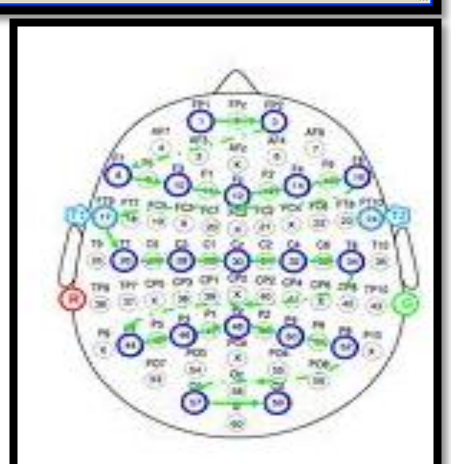


EEG STPR





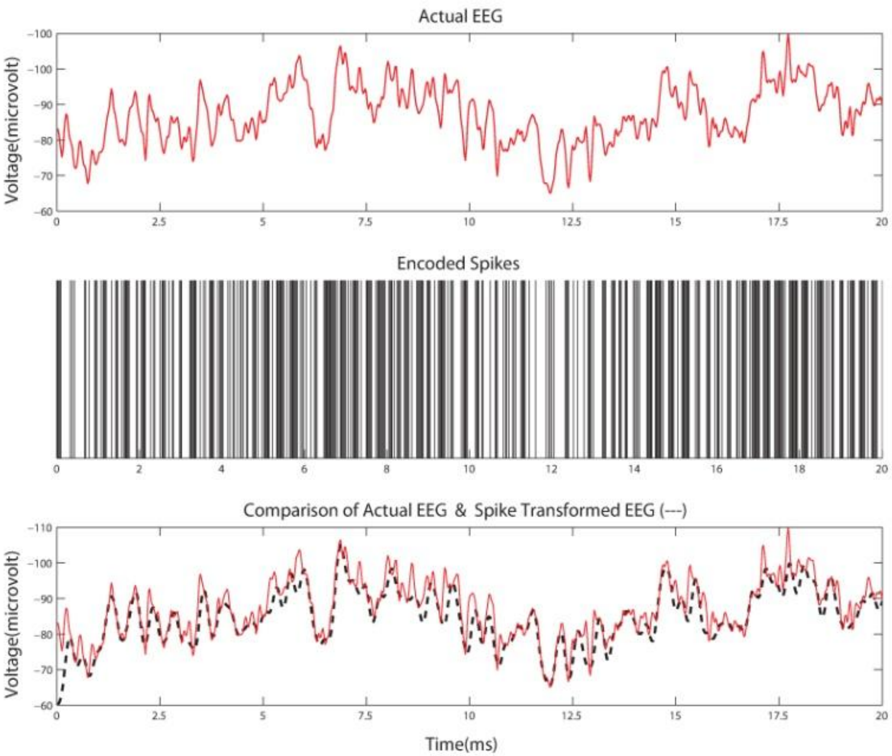
(McFarland, Anderson, MÜller, Schlögl, Krusienski , 2006)

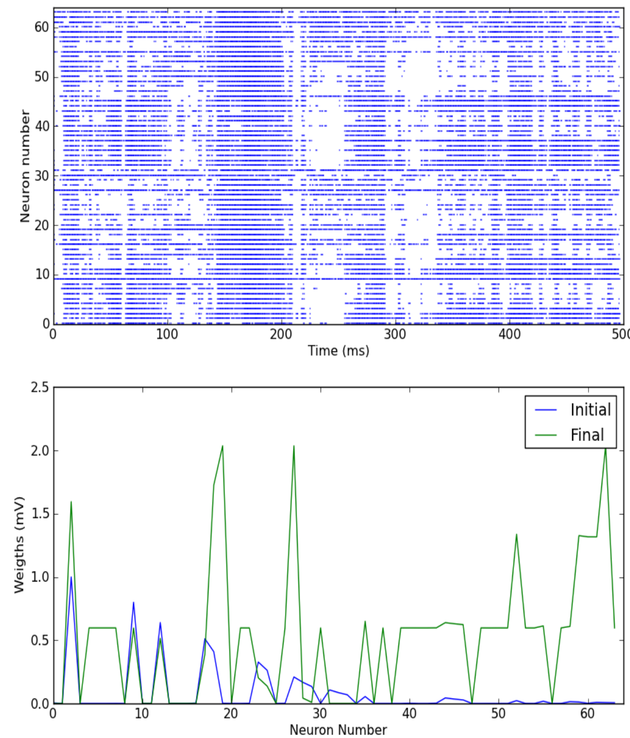


http://www.nuroshop.com

EEG STPR for four stimuli using deSNN vs probabilstic LSM reservoirs + MLP classifier

Data collected in RIKEN by van Leuwen: EEG of a *single subject* is measured when four different stimuli are presented: image; sound; both, none.



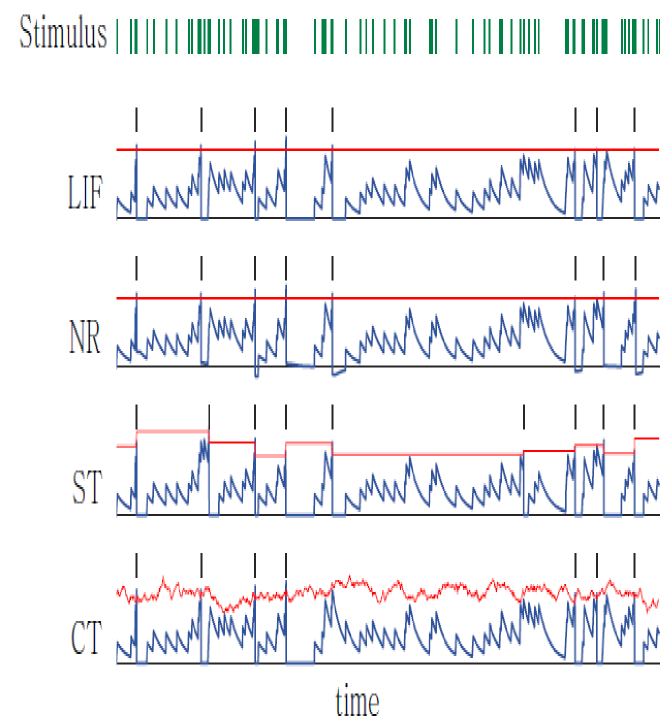


(a) Encoding EEG signals into spikes using the BSA (Ben's Spike Algorithm) by Schrauwen and van Campenhout, 2003 (N.Nuntalid and N.Kasabov, ICONIP2011; Nuntalid et al, Evolving Systems, 2012)

(b) Exemplar spike trains on all 64 inputs for one EEG data sample (upper figure) and the weights changes of one output neuron (dedicated to this input sample) during the one pass presentation of the spike inputs to the DepSNNs model..

Results on the case study problem of EEG STPR

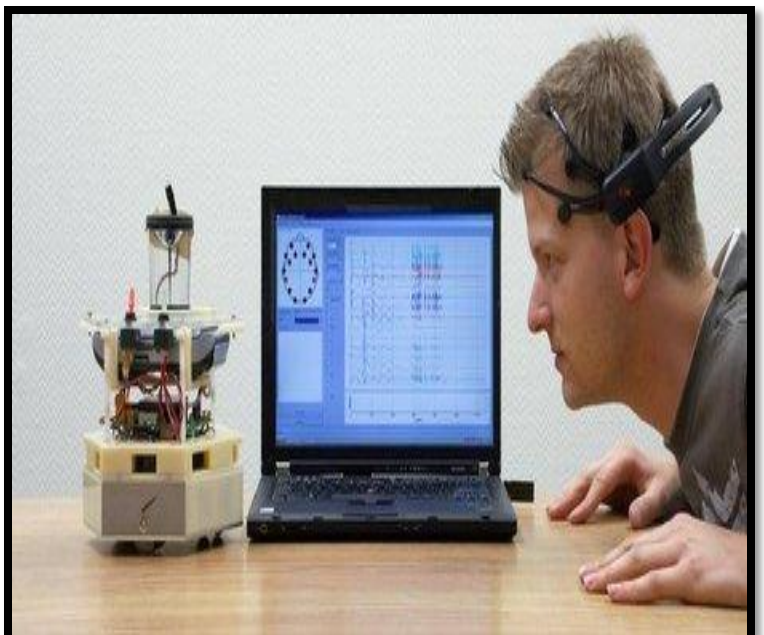
Classifier	Classifier only	LMS reservoir + classifier			
	Accuracy	LIF	NR	ST	CT
NaiveBays	66.9%	75%	75%	75%	75%
MLP	64.87%	50%	50%	75%	50%
DepSNNs	**75%**				



Note: The brain state for ‘No stimulus’ was completely misclassified by all classifiers.

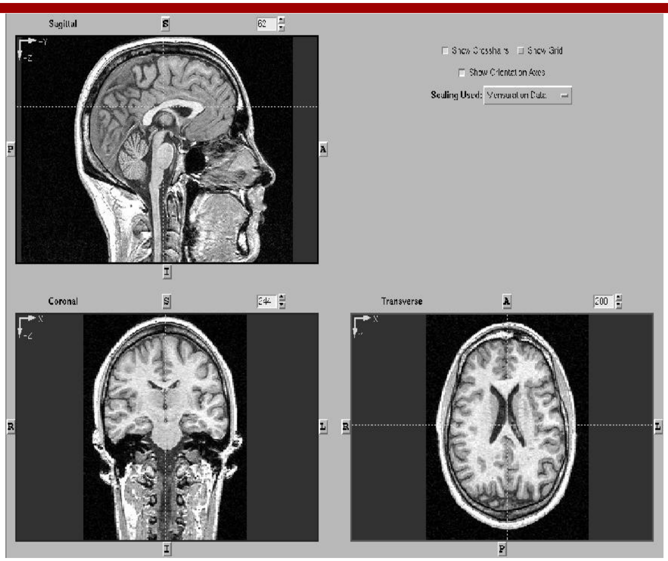
BCI

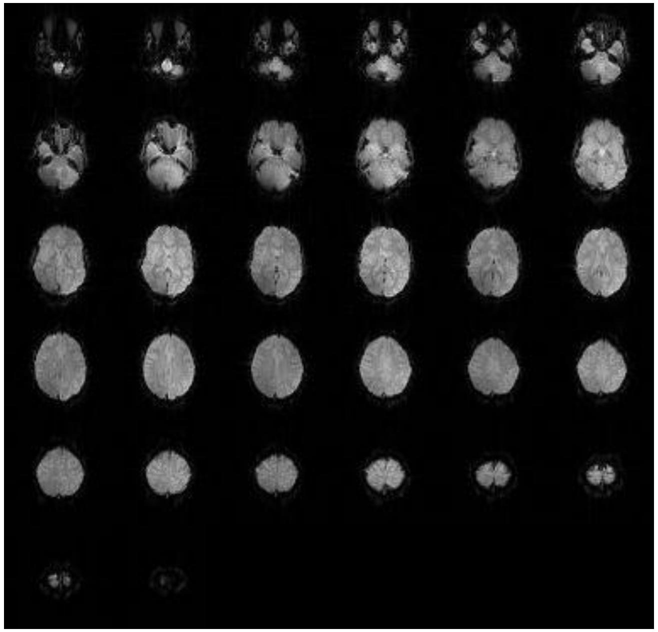
- Brain-Computer Interfaces (BCIs) are interfaces that allow humans to communicate directly with computers or external devices through their brains (e.g. EEG signals)
- Experiments with the WITH robot from KIT, prof. Yamakawa (S.Schliebs)
- Neuro-rehabiltation and neuro-prosthetics (with CAS, Z-G Hou)
- Collaborative work with U.Aveiro (P.Georgieva)



http://www.nzherald.co.nz

STPR of fMRI data





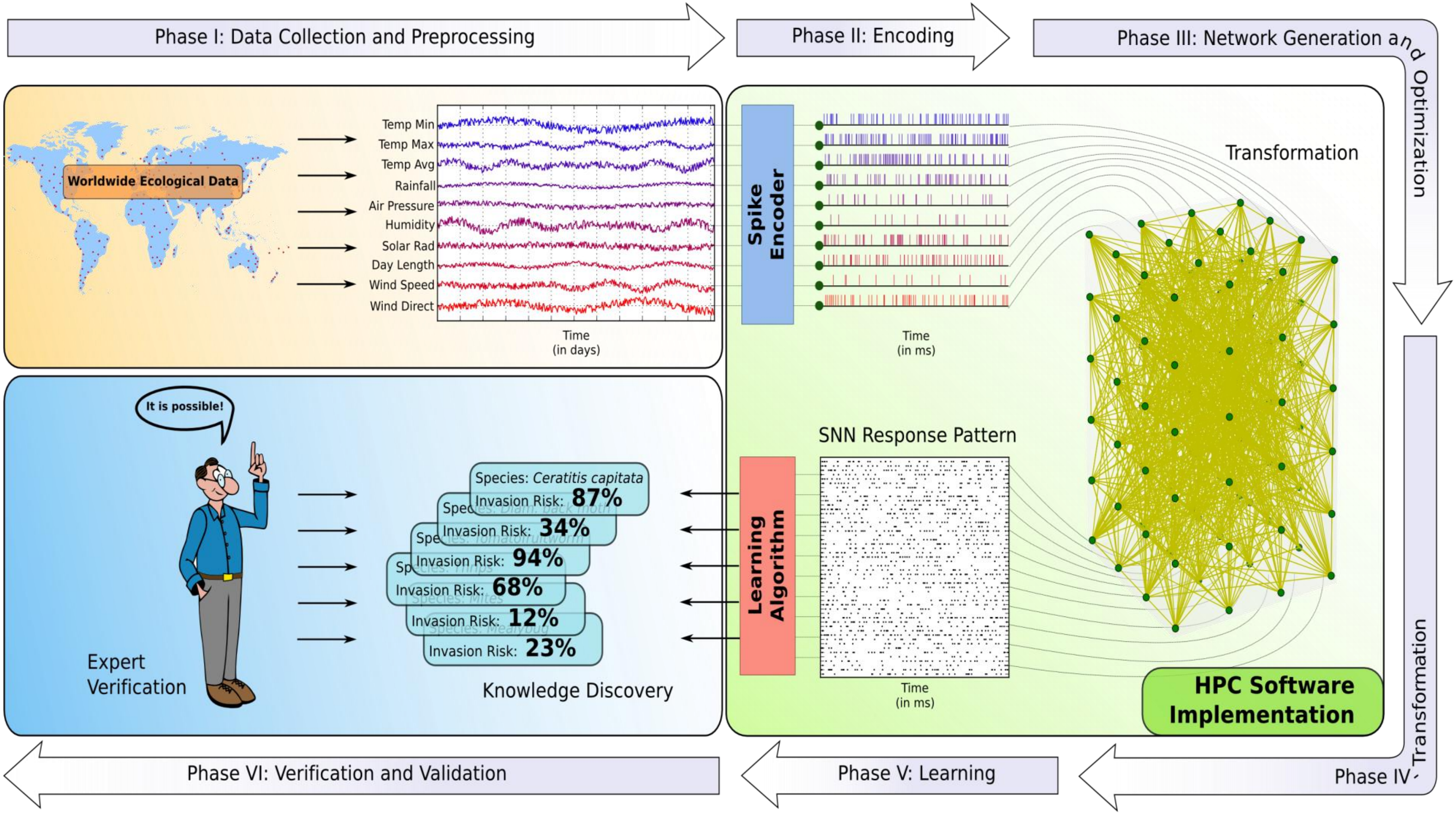
- fMRI images are taken in sequence and over time either vertically or horizontally (sagittal / coronal / axial)
- Each image in the sequence is called a slice which represents a spatial activity of the brain
- A collection of slices → a volume
- A slice is made up of voxels, (individual cube elements), which can have a spatial resolution from as high as 1x1x1 mm^3 (small voxels) to as low as 7x7x7 mm^3 (large voxels).
- fMRI is a 4D SSTD (3D spatial dimensions and 1D time)
- Sona, Avesani et al, IJCNN, 2011

Pictures from: http://www.fmrib.ox.ac.uk

EvoSpike for Ecological STPR

Example: Estimating the risk of establishment of invasive species

(early publication: S.Schliebs, S.Worner et al, Neural Networks, No.22, 2009)



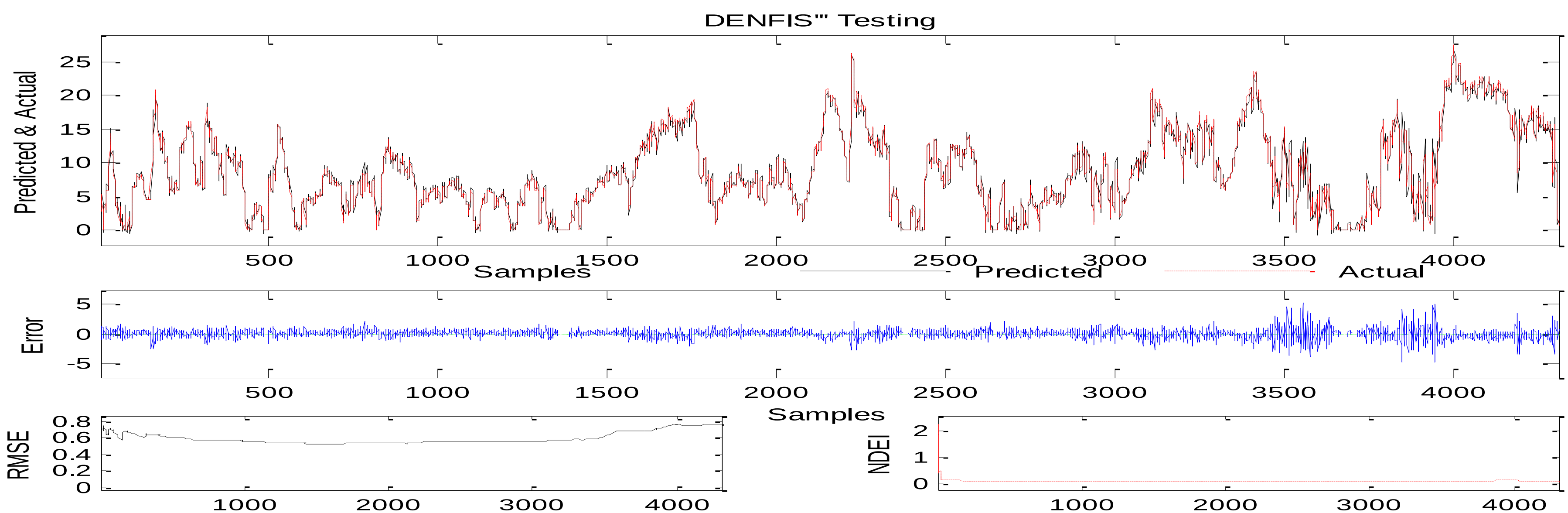
Adaptive, autonomous robot technologies

(e.g. work by R.Duro, P.Angelov, KIT Japan, U.Ulster, NASA, other)

Wind energy prediction and the prediction of extreme environmental events

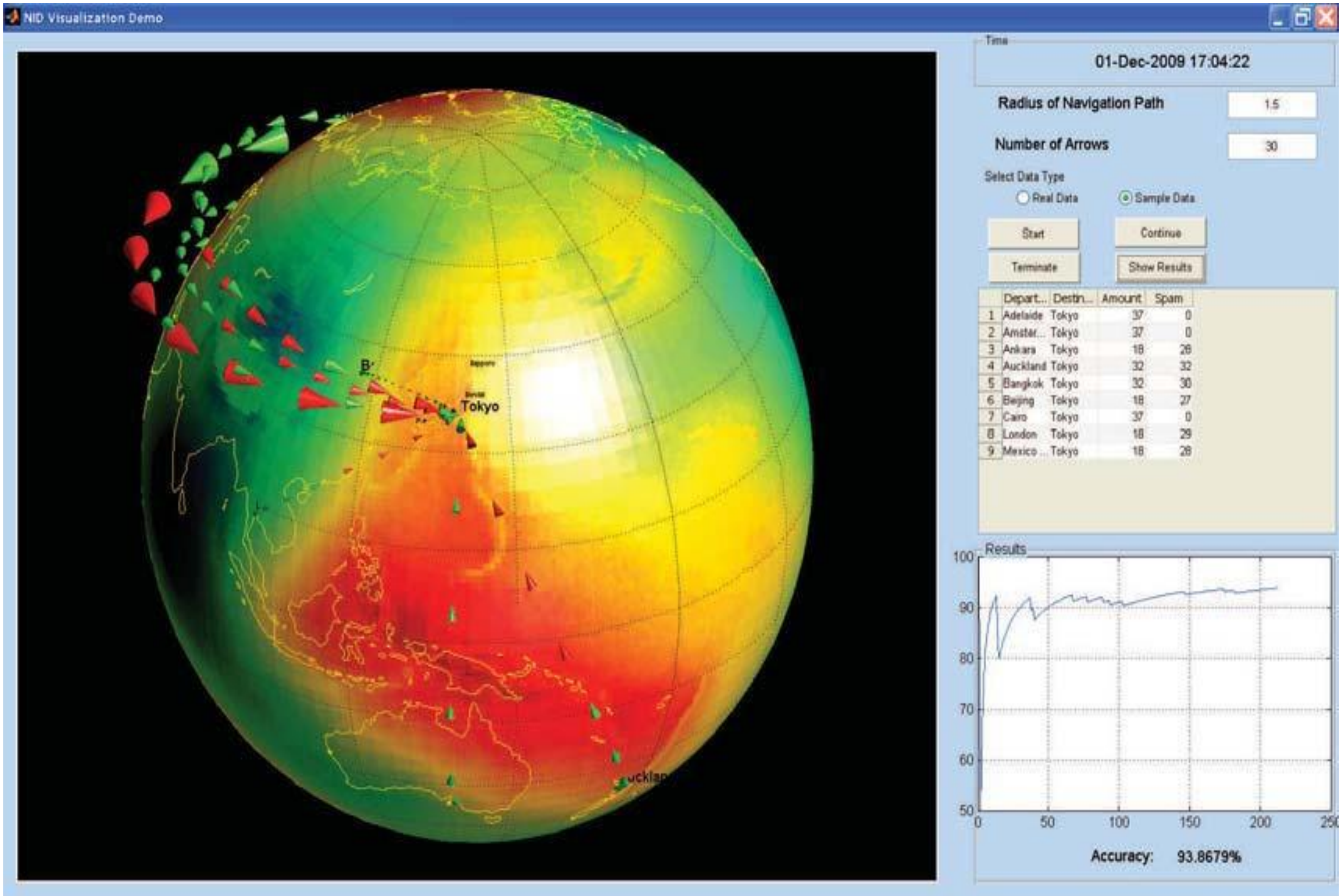
New Zealand

Xinjiang, China (中国新疆)



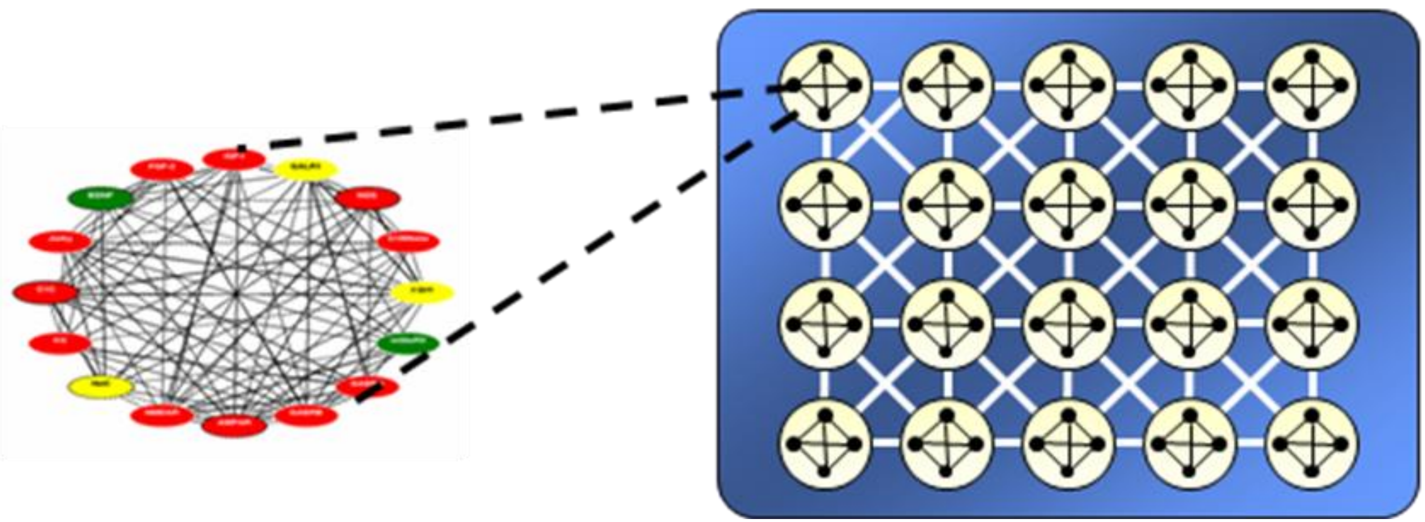
nkasabov@aut.ac.nz

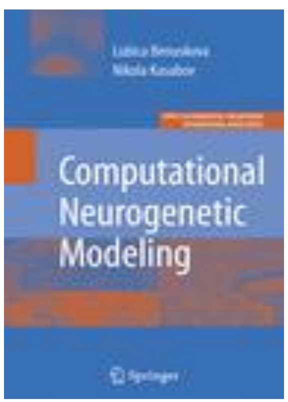
Cybersecurity



Computational Neuro-Genetic Modelling

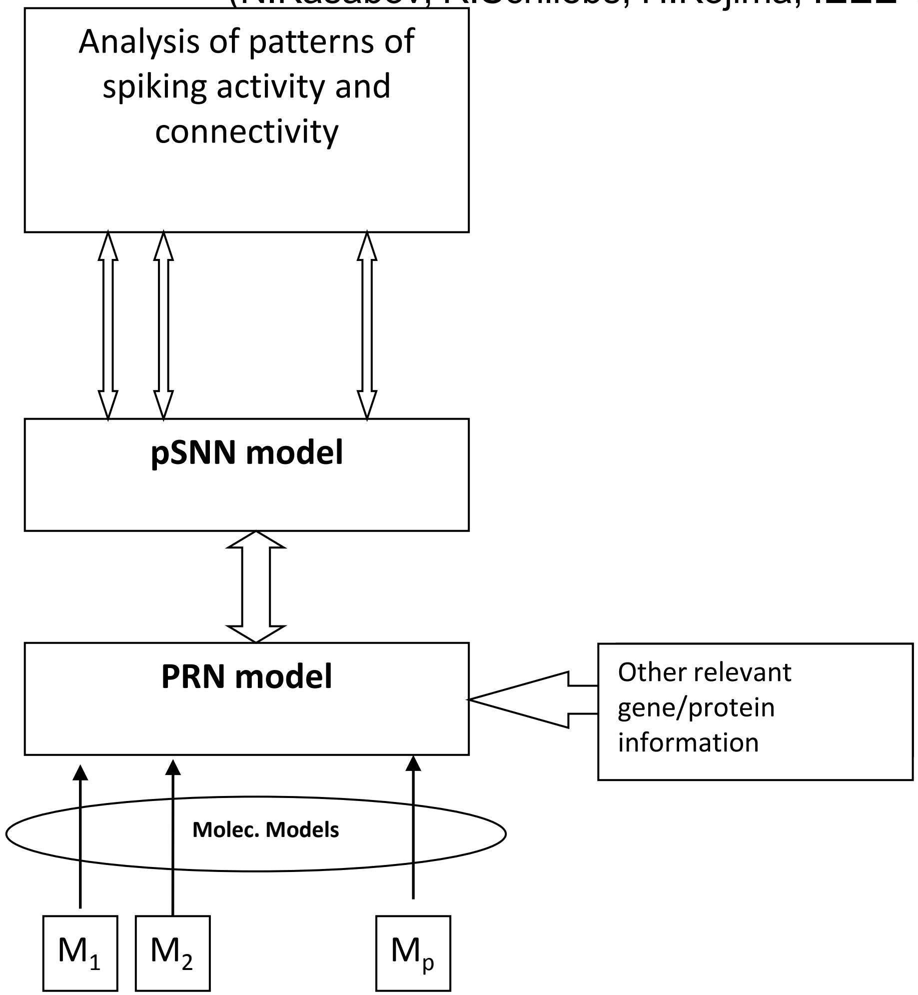
- SNN that incorporate a gene regulatory network (GRN) to capture dynamic interaction of genes related to neuronal activities of the SNN.
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.
- The GRN and the SNN function at different time scales.
- The challenge is how to integrate a GRN model into a SNN model for an efficient CNGM.
- Work by: Benuskova and Kasabov (2007); Meng and Jin (2011)

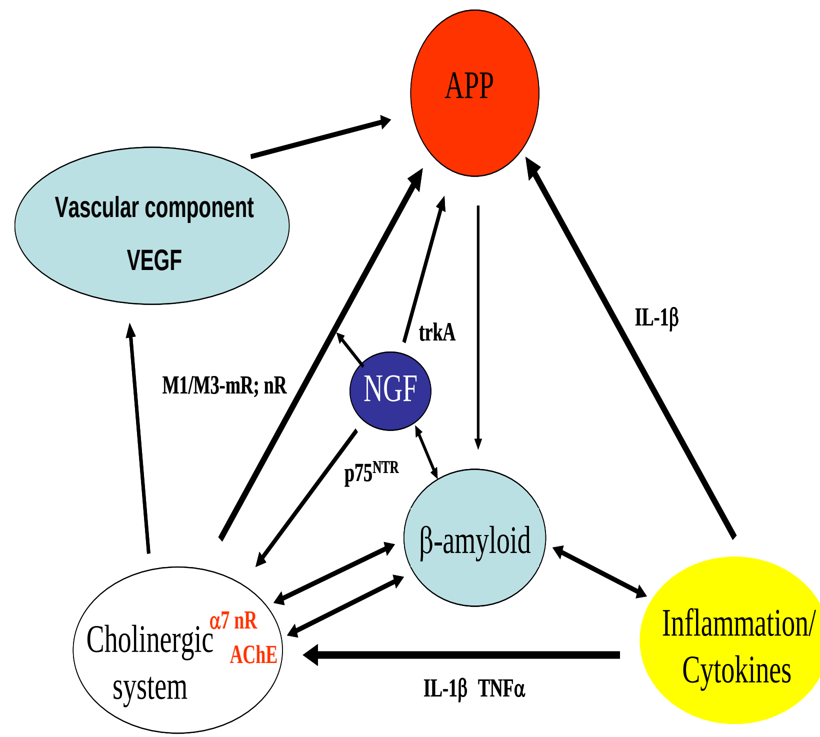




Neurogenetic modelling for cognitive and emotional robots and AD. Can AD disease be predicted at an early stage?

(N.Kasabov, R.Schliebs, H.Kojima, IEEE TAMD, v.3, No.4, December 2011)





Personalised Modelling (PM) systems
Personalised brain models

N. Kasabov and R.Hu, Integrated Optimisation Method for Personalised Modelling and Case Study Applications for Medical Decision Support, *J. Functional Informatics and Personalised Medicine*, 2011

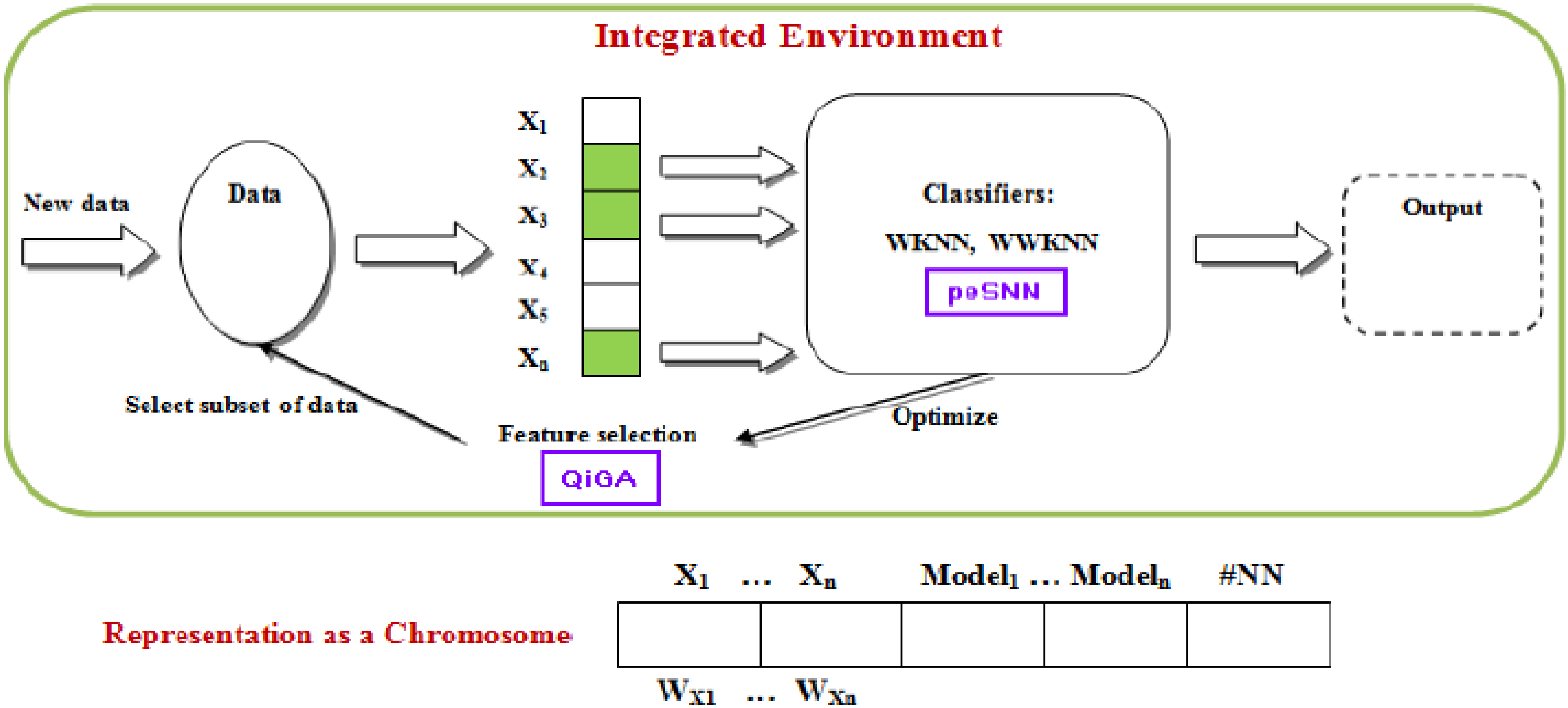
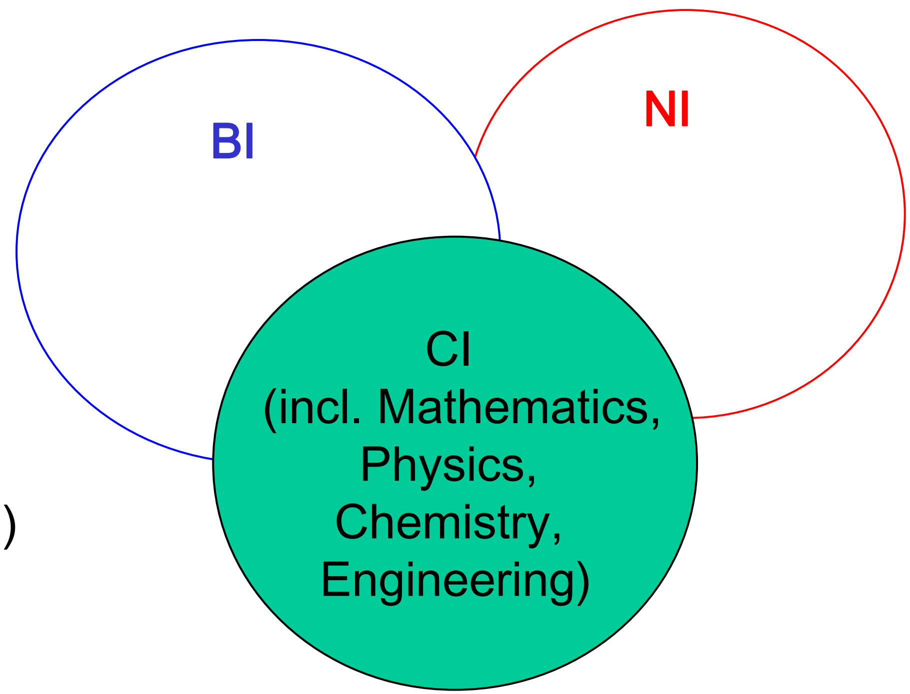


Fig.1: An overview of the novel personalised modelling system.

5. Future Directions

- Implementation of EvoSpike on a SNN supercomputer (e.g. SpiNNacker, U.Manchester) for a large scale *mapping, learning and mining of spatio-temporal data.*
- EvoSpike chip design for specialised applications (G.Indivery, INI/ETH/EZH)
- Applications: Engineering; BCI; Neuroprostetics; Neuroeconomics; Environment.

- Further interdisciplinary research in the three areas of CI, BI and NI
- The Springer Handbook of Bio-Neuroinformatics, 2013 (N.Kasabov, ed)
- The Springer Series of Bio-Neuroinformatics (N.Kasabov, ed)
-



6. References

N.Kasabov, Evolving connectionist systems: The Knowledge engineering approach, Springer 2007 (first edition 2003)

N.Kasabov, Foundations of neural networks, fuzzy systems and knowledge engineering, MIT Press, 1996

N.Kasabov, Evolving Intelligence in Humans and Machines: Integrative Connectionist Systems Approach, IEEE CIS Magazine, 2008, vol.3, No.3, pp. 23-37

N.Kasabov, Integrative Connectionist Learning Systems Inspired by Nature: Current Models, Future Trends and Challenges, Natural Computing, Springer, V.8, 2009, 2, pp. 199-210,

N.Kasabov, To spike or not to spike: A probabilistic spiking neural model, Neural Networks, v.23, 1, 2010, 16-19

N.Kasabov and R.Schliebs and H.Kojima, IEEE TAMD, v.3, No.4, December 2011

L.Benuskova and N.Kasabov, Computational neurogenetic systems, Springer, 2007

M.Defoin-Platel and S.Schliebs and N.Kasabov, A versatile quantum inspired evolutionary algorithm, IEEE Trans. Evolutionary Computation, 2009

N.Kasabov, Global, local and personalised modelling and profile discovery in Bioinformatics: An integrated approach, Pattern Recognition Letters, v.28, 6, 2007, 673-685

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- Marie Curie FP7 project ‘EvoSpike’ hosted by the Neuromorphic Cognitive Systems Group of the Institute for Neuroinformatics at the ETH and University of Zurich: http://ncs.ethz.ch/projects/evospike
- The EANN 2012 organisers

SEVENTH FRAMEWORK PROGRAMME

MARIE CURIE ACTIONS

KEDRI: The Knowledge Engineering and Discovery Research Institute at AUT (www.kedri.info), established 2002